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School of Engineering

Online Regime Switching Vector Autoregression Incorporating Spatio-temporal Aspects for Short Term Wind Power Forecasting

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January 28th, 2018

Aalto University
School of Engineering
Nordic Master in Innovative Sustainable Energy Engineering – Energy Systems

Thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Technology.

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Abstract of master's thesis

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Title of thesis Online Regime Switching Vector Autoregression Incorporating Spatio-temporal Aspects for Short Term Wind Power Forecasting

Master programme Innovative Sustainable Energy Engineering **Code** IA3025

Thesis supervisor Professor Mika Järvinen

Thesis advisor(s) Dr John Millar

Date 28.01.2018 **Number of pages** 60 **Language** English

Abstract

This master thesis examines short term wind power forecasting time series models focusing on regimes conditioned to meteorological conditions and the incorporation of spatio-temporal aspects. Novel regime switching autoregressive and vector autoregressive models are proposed, implemented in a .NET framework, and evaluated. The vector autoregressive framework takes advantage of cross-correlation between sites incorporating upstream online production information from all wind farms within a given region. The regimes are formed using K-means clustering based on forecast meteorological conditions. Each of the proposed models are fit to hourly historical data from all of 2015 for 24 wind farms located in Sweden and Finland. Forecasts are generated for all of 2016 and are evaluated against historical data from that year for each of the 24 wind farms. The proposed models are successfully implemented into the .NET framework of Vitec Software's Aiolos Forecast Studio, which is widely used in the Northern and Western Europe. Vitec's Aiolos wind power forecast model is based on an ensemble of numerical weather prediction models and adaptive statistical machine learning algorithms. The proposed models are found to have significantly lower mean absolute error and root mean squared error compared to the Aiolos model and autoregressive model benchmarks. The improved short term wind power forecast will inform operation and trading decisions and translate to significant reductions in balancing costs for Vitec's customers. The improvement is valued at as much as between 9.4 million Euros to 42.3 million Euros in reduced balancing costs. Spatio-temporal aspects for wind power forecasting is shown to continue to be promising for improving current state-of-the-art wind power forecasting.

Keywords Wind power, short term forecasting, spatio-temporal, regime switching, vector autoregression.

Contents

1. Motivation

Failure to mitigate climate change is one of the greatest risks currently facing humanity. Catastrophic impacts to humanity and natural systems due to climate change are increasing in severity with continued emissions of green house gases and land use changes. Human systems and natural systems are inextricably linked and are both extremely vulnerable to climate change. [1]

There is a dramatic paradigm shift occurring in the world's energy systems driven by both the need to tackle climate change and technological development.This paradigm shift is characterised by decarbonisation, electrification and decentralisation. Wind power is playing an important role in the decarbonisation of the energy system. The cumulative installed capacity of wind power was 487 GW at the end of 2016 [2]. The International Energy Agency estimates that a share of 18% of global electricity will need to be provided by wind power by 2050 to keep global warming below 2°C [3].

Wind power with its stochastic and variable nature presents challenges to integrating wind power into power systems and electricity markets. Wind power generally increases the total variability of the power system and increased flexibility of the power system is needed to maintain the balance between production and consumption of electricity [4]. The variability and limited predictability of wind power make accurate wind power forecasts essential for reliable and economic power system operation. Errors in the wind power forecast increases required balancing services, namely regulation power reserves. With increasing penetration of wind power in power systems these challenges become more critical. Reducing error in the forecasts for wind power reduces balancing costs and facilitates the integration of higher penetration levels of wind power in a power system. [5]

2. Introduction

In this introduction, the applications and state-of-the-art of wind power forecasting and introduced before discussing current efforts towards improving the state of the art of wind power forecasting. Forecast evaluation is discussed in Section 2.4. A thorough discussion and literature review of spatio-temporal aspects for wind power forecasting can be found in Section 2.5.

The case study and input data is introduced in Section 3.1. The development and justification of each of the proposed models is given in Section 3.2. A discussion of the implementation, software development and Aiolos wind power forecast model are in Section 3.3.

The results and analysis of the proposed models evaluated with the case study follows in Section 4. A discussion of the contribution and significance of this master thesis, as well as a discussion of the limitations and future research and development is in Section 5. The final conclusions are in Section 6.

2.1. Wind Power Forecasting Applications

Historically, almost all electricity production in power systems globally was generated from the energy sources of coal, natural gas, other fossil-fuel derived products, biofuels and hydro. With the exception of electricity production from run-of-the-river hydro, electricity production from these sources is for the most part determined by the will of the owner.

The electricity production from wind power is inherently stochastic and its electricity production is determined not only by the will of the owner but by wind resource. As power systems integrate increasing amounts of wind power, the operation of the power system needs to be more flexible to compensate for the increased variability and uncertainty [4]. The total variability can be separated into two components, the variability of the wind resource itself, and the variability of the wind power forecast error.

The fundamental characteristic for the reliable delivery of electricity is power system stability. It is the ability of an electric power system to regain a state of operating equilibrium after being subjected to a physical disturbance [6]. Changes in load and production occur continuously and in the frame of reference of power system stability, are defined as small disturbances to the equilibrium between load and production. These production disturbances increase with increasing wind power penetration and increased wind power forecast error. Improved wind power forecasts with less error can thus reduce the pressure on the power system to adjust to these changing conditions and to maintain stability.

The efficient operation of a power system requires forecasts of the demand, production and network conditions from seconds ahead to years ahead. Electricity system participants with wind power in their respective power systems use wind power forecasts for their operations, trading, and planning. These participants include the network system operators, utilities, balance responsible parties, traders, and independent power producers. A survey of system operators regarding wind power integration found that 94% of the respondents indicated that the integration of a significant amount of wind power will ultimately depend on the accuracy of wind power forecasts [7].

Until the end of the twentieth century, power systems globally were organised by state-owned, vertically-integrated utilities that were responsible for the generation, transmission, distribution, and retail. In contrast, in a modern power system activities are often separated. Competition in generation and retail is often encouraged through markets. Transmission and distribution as natural monopolies are regulated and are managed by system operators. Modern electricity markets often take the form of a centralised market in which producers and consumers submit bids and offer functions to a central market operator [8]. In some countries reserve capacity markets exist in parallel to energy markets where participants are paid proportional to the available capacity. There are also electricity markets for longer term financial contracts such as forwards, options, and derivatives. The electricity markets that are most relevant for short term wind power forecasting are day-ahead, intra-day, and balancing markets [5].

In day-ahead markets, also known as forward markets and spot markets, market participants submit bids to buy and sell electricity through price-quantity pairs for each block of time of the following day. The aggregate buy and sell curves are sorted by increasing and decreasing prices respectively by the market operator. The intersection between these two curves sets the system price by which the market is cleared. Sale bids with a price lower than the system price are accepted, and buy bids with a price higher than the sytem price are accepted. Market clearance that considers transmission network constraints in the market clearing procedure sets locational prices for each area or node of the power system rather than a single system price. [5]

J. Miettinen and H. Holttinen recently studied day-ahead hourly forecast errors from Finland, Norway, Sweden and Denmark and the impacts of wind power plant dispersion on forecast errors in areas of different sizes [9]. They found that mean absolute errors normalised to total energy production of the hourly resolution forecasts reduce from the value of 31.3% for a single region to 9 % for the whole of the Nordic region. These errors would represent significant balancing demands on the power system if it were not for being able to later adjust day-ahead contract positions on intra-day markets. Wind power forecast errors reduce with shorter lead times and thus the original positions on the day-ahead market can be adjusted on the intra-day and balancing markets [10]. Intra-day and balancing markets are seen as essential to the large scale integration of wind power [11].

Balancing markets, also known as real-time markets or regulation markets, are the last chance for power system participants to participate in balancing production and demand in the power system before the inherent stability of the transmission and distribution network itself is relied upon. The balancing market handles imbalances due to forecast errors and is used to alleviate congestion problems during the operating hour by the activation of regulating power from other market participants [5]. These balancing services include automatic frequency controlled reserves, load frequency reserves, and regulation power reserves. These services are also known as primary, secondary and tertiary regulation respectively. Improved short term wind power forecasts can reduce the required balancing needs [12]. The balancing needs can become critical if there is insufficient flexible and competitive regulation capacity available through the balancing markets [5]. Wind power forecasts with reduced error thus not only reduce the associated balancing costs, but facilitate higher penetration of wind power.

The latest summary report from the International Energy Agency Wind Task 25, Design and Operation of Power Systems with Large Amounts of Wind Power, reports information on system balancing costs from studies on Canada, Denmark, Finland, Germany, Ireland, Norway, Sweden, the UK, and the US [4]. It is reported that the system balancing costs due to wind power forecast error is between 1 to 4.5 Euro /MWh for wind penetrations of up to 20% of gross energy demand; this is approximately up to 10% of the wholesale value of the wind energy [4]. Lower balancing costs can be achieved through improved wind power forecast performance, the allowance of interconnection capacity to be used for balancing purposes, aggregating wind farms over larger geographical regions, and scheduling closer to the delivery time [4].

2.2. State-of-the-art Wind Power Forecasting

Current state-of-the-art wind power forecasts are based on a combination of physical and statistical models. Giebel et al. comprehensively reviewed the state of the art in the short term prediction of wind power; for further reading the author directs the reader to this work which reviews more than 380 journal and conference papers [10]. Models with an emphasis on a statistical approaches and online measured power data outperform models with emphasis on physical approaches for lead times up to 3 to 6 hours ahead. Final wind power forecast models thus seek to optimally combine wind power forecast models depending on the lead time of interest.

Models with emphasis on physical approaches are based on outputs from mesoscale and microscale Numerical Weather Prediction (NWP) models, namely wind speed and wind direction. Physical laws are used in NWP models to forecast the weather. Predicting a future state of the atmosphere is achieved fundamentally by starting from the assimilation of the observed weather and integrating the governing partial differential equations accounting for dynamic, thermodynamic, radiative and chemical processes. State-of-the-art mesoscale NWP providers forecast down to a geospatial scale of 1 to 2 kilometres, with a temporal scale of 30 minutes to 1 hour resolution, and are updated every 1 to 3 hours [13].

Statistical treatments are also used at multiple stages of a modelling process that has emphasis on physical aspects. Model output statistics and ensembles are used to reduce bias and error in the outputs from the NWP. Wind speed and direction are then downscaled to the specific location and hub height of the turbine from an optimised selection of the surrounding NWP grid points and elevation data. This downscaled wind speed and direction is then converted to power with a power curve. The power curve is estimated from the historical statistical relation between forecasted wind speed and direction and measured power. If historical power measurements are not available, the manufacturers power curve can be used, although almost always with poorer performance [10]. It is at the next step that the line between models with an emphasis on physical approaches and statistical approaches starts to blur, as both model approaches utilise online measured power data to improve model output statistics using adaptive recursive methods.

For shorter forecast horizons and where the recently measured online power data is available the measured data is used as the key input, taking the form of an explicit statistical model using advanced time-series approaches of classical time-series analysis or less frequently, artificial neural networks [10]. While artificial neural networks show similar results to classical time-series approaches, they do not permit a clear interpretation of the underlying processes being modelled [14]. Gallego et al. (2011) [15] found that making generalised autoregressive models conditional to local wind direction captured the impact of the wind direction on the wind variability. Additionally, they found making the models conditional to wind speed captured the non-linear behaviour related to the power transformation process . Trombe and Pinson (2012) [16] examined the predictive performance of the most recent approaches in the wind power forecasting literature for very short lead times. They considered combinations of linear auto regressive models with various regime switching models, and offsite predictors. The approaches were extended to a probabilistic framework using the generalised logit normal distribution. Trombe and Pinson (2012) found that hidden Markov-Regime switching models had superior predictive performance over threshold regime switching models based on observable lagged values, confirming the findings of Pinson et al. (2008) [17]. The hidden Markov-Regime switching models are based on an unobservable process that represents a hidden weather regime. Trombe and Pinson (2012) suggest that integrating higher spatio-temporal resolution information could further improve the predicative performance [16].

When upscaling from a single turbine to a wind farm the wake losses can be accounted for using statistical and semi-empirical methods [10]. Upscaling from a single wind farm to a group of wind farms in a point forecast framework can be achieved using simple summation. Alternative approaches include using representative farms as input in upscaling models.

Probabilistic forecasts have been shown to provide additional value over point power forecasts [18] [16]. Given the stochastic nature of wind power, there exists an intrinsic uncertainty in the wind power generation process and its prediction. A probabilistic framework results in more optimal decisions, both in terms of power system management and electricity trading [19] [12].

In a probabilistic framework, upscaling from a single wind farms marginal distribution to form the probabilistic forecast for a group of windfarms cannot be achieved with simple summation. Marginal distributions can only be summed if they are independent. The aggregated error of a group farms is less than the error of a single farm. This feature is explained by two effects; the aggregated production is smoother due to the partially uncorrelated series making its prediction easier, and secondly the forecast errors are partially uncorrelated [9]. As wind power production is correlated in space and in time, probabilistic forecasts which provide information about the uncertainty of wind power forecasts for various locations and lead times, as well as about their spatio-temporal dependencies, can improve both power system management and trading decision-making processes that rely on wind power forecasts. This can be achieved for example through random field based statistical methods [20] [21].

In a recent survey of wind power forecast end users conducted as a part of International Energy Agency Wind Task 36 on Forecasting, less than 10% of end users currently make use of probabilistic forecasts [22]. The main reason attributed to not transitioning to probabilistic forecasts despite their clear benefits is difficulty interpreting the forecasts and a lack of transparency in regulations.

2.3. Towards Improving State-of-the-art Wind Power Forecasting

There are many research areas with potential to improve the current state of the art in wind power forecasting, many of which are identified in the International Energy Agency Wind Task 36 Wind Power Forecasting [22]. Improved forecast skill of Numerical Weather Prediction (NWP) model outputs has significant potential to improve wind power forecasting. Potential developments include: better ensemble variability calibration, more rapid update cycle, improved model physics, and finer spatial and temporal resolution [22]. The key challenge areas for NWP advances in prediction performance can come from scientific and technological innovation in computing, development of the representation of physical processes in parameterizations, integrating advanced data assimilation algorithms, and improved characterisation of uncertainties through ensemble methods [13]. Other issues such as the prediction of icing [23] and ramp events [24] are important. Another research area regards capturing the interaction between wind farms wake effects as wind farms continue to increase in size and the wakes form one farm can interact with another. Additionally, wind farm wake effects could be included in NWP models; as wind farms increase in size, particularly offshore wind farms, they are becoming large enough to have a noticeable effect on local weather [22].

International Energy Agency Wind Task 36 Wind Power Forecasting identifies spatio-temporal forecasting as an area to improve prediction performance; and indicates that while several methods have been researched, they have yet to be implemented in operational models and further methods should be investigated [22]. Further, the works have only been verified for high wind regions where the driving wind comes from the ocean such as Denmark, Portugal, and Southern Australia, and thus case studies are required for other regions. This online upstream information can be sourced from anemometer measurements, radar, lidar, or as studied in this master thesis, the wind farm power production data.

2.4. Forecast Evaluation

For point forecasts, mean absolute error (MAE) and root mean squared error (RMSE) are the most common performance measures [16]. MAE gives the same weight to all errors, while the RMSE penalizes variance as it gives errors with larger absolute values more weight than errors with smaller absolute values. The two measures together provide information for expected balancing costs and some insight of the distribution of errors [25]. Madsen et al. (2005) [26] propose a common set of performance measures including bias, MAE, RMSE as well as to include the error distribution as a histogram. While this thesis focuses on point forecasts, it is worth noting that probabilistic forecasts are inherently more difficult to evaluate; Pinson et al. (2007) [27] propose a framework for the evaluation of probabilistic forecasts to provide information on the reliability, sharpness, resolution and skill.

The performance measures of wind power forecasts are often made normalised to the installed capacity both in the market place and in literature [28]. Normalising measures to the installed capacity makes wind power plants with lower capacity factors to appear to have better performance scores when compared high capacity factor wind power plants. Further, the capacity factors of the wind power plant are often not presented together with the evaluation making interpretation of the forecast errors for power system studies difficult [10]. Normalising performance to the capacity overcomes the issue faced when normalising to the production in the case where the production is 0. Normalising the performance to the cumulative production over the period of evaluation similarly solves this problem, and is increasingly done both in research and the market place in the evaluation of solar power forecasts [29]. Madsen et al. (2005) [26] recommend normalising to the installed capacity and not the production arguing that for new wind farms the installed capacity information is easy to assess, while the mean production is hard to know with sufficient accuracy. This master thesis presents performance measures of MAE and RMSE which are normalised to the installed capacity for ease of comparison to other research for the reader. The capacity factor information is also provided. For the case study of this thesis, the installed capacity is 329 MW and the capacity factor is 0.298. Normalising the MAE and RMSE to the mean production would lead to error scores given by 1 / 0.298 = 3.36 times higher than scores normalised by the installed capacity.

The end user of the forecast defines what constitutes a good forecast [9]. Electricity market participants seek to maximize their profit by minimizing the balancing costs. This leads to a mean absolute error measure being more important evaluated over the temporal resolutions of the blocks in which electricity is traded [5]. Further, overestimation or underestimation in production can be incentivised if the balancing costs are expected to be a difference between up-regulation and down-regulation prices [19]. Power system operators seek to operate the power system reliably by avoiding significant forecast errors while also minimizing the total errors and the use of regulating power [5]. Among the most important features to forecast from a power system perspective are sudden and pronounced changes and ramp events, for example due to a passing storm front, which has been a growing area of research [10].

The interpretation of the predictive performance of wind power forecast models requires care. The variability of the underlying wind power production is strongly correlated with the difficulty in forecasting the power production [30]. A non-exhaustive list factors affecting both variability of the underlying wind power production includes: the design of the wind farms considered; the number of wind farms considered and the total power capacity together with the geographic spread and cross correlation of the wind farms; the capacity factors of the wind farm, the topology of the surroundings and whether the farms are onshore, near-shore, or offshore; the climate, weather, and season; the lead time considered; and the temporal resolution of the forecast [30] [9]. Forecast error decreases with increasing geographic spread due to aggregated production being smoother due to the partially uncorrelated series making its prediction easier, and secondly the forecast errors are also partially uncorrelated [9]. Increasing temporal resolution also smoothens the group wind power production and forecast error just as it does with increasing spatial domains. Wind power production averaged over shorter temporal domain of 1 to 5 minutes will show higher variability than wind power production averaged over an hour [10]. The characteristics of the power curve including cut in speed, output speed, and cut-out speed as well as the various gradients along the power curve influence the difficulty of forecasting wind power. Steeper power curves with higher cut in speeds are typically more difficult to forecast because small changes in the wind speed result in larger changes in power produced. Certain weather and associated seasons are more difficult to forecast than others such as major storms and high instability [10]. Wind power forecasting models evaluated for wind power plants in regions with more challenging meteorological conditions will show poorer model performance.

Given the difficulty in obtaining good information on all of potential factors influencing predictability when comparing models that have been evaluated on different sets of wind turbines, caution should be exercised. The practice of comparing one model performance to another model or benchmark models with the same data set is a useful tool for the comparison of predictive skill. Simple persistence forecasts for the very short term wind power forecasts or simple first order auto regressive forecasts can be used benchmark models for short term wind power forecasting [26] [10] [31]. It is worth noting however that persistence and auto regressive forecasts are not a static benchmarks, wind farms with higher autocorrelation will have better performing persistence and auto regressive forecasts. Further, persistence and auto regressive models vary depending on the temporal resolution on which they are based. Persistence and autoregressive models are used as benchmarks herein.

2.5. Spatio-temporal Aspects for Wind Power Forecasting

Current state-of-the-art short term wind power forecasts have been shown to be improved by accounting for the spatio-temporal propagation of wind power or wind power forecast errors between wind farms [32] [31].

For lead times of 3 to 6 hours ahead current state-of-the-art short term wind power forecasts rely heavily on wind speed forecasts issued by Numerical Weather Prediction (NWP) [10]. NWP models are typically only issued every two to three hours [13] due to high computational expense of data assimilation and physical model processes utilising millions of inputs from many different sources including ground weather stations, weather balloons, and satellites. The time from initial observation are recorded to when the data assimilation and NWP model processes are completed can be up several hours on high-performance computers despite that the highest-performance computers employed in NWP place in the top 20 of the most powerful systems in the world [13]. Weather is chaotic, chaos theory even has roots in efforts to quantify atmospheric predictability [33]. The more time between observation and forecast periods, the more chaos can enter the system; and this is part of the reason that weather forecast skill beyond a few days ahead deteriorates rapidly. The challenges of this chaotic nature exists already for forecasting several hours ahead. The first minutes of the newly issued meteorological forecast can be based on observations that are several hours old, which can extend up to being 6 hours old before the next NWP forecast update is issued. This weakness can be computationally efficiently addressed by utilising spatial temporal aspects, taking upstream online information that is as little as several seconds old and incorporating that directly into the wind power forecast. This allows more recent spatio-temporal information that was previously only available through NWP outputs for longer time horizons to be available to very short term forecasting.

Wind power production data from wind power plants is an attractive predictor of power output because there is no conversion or scaling required [34]. In contrast, wind speeds recorded by small aenometers are more susceptible to turbulence from nearby structures and micro currents in the wind flow. Attaining quality live wind speed observations at hub height is challenging. Radar and Lidar development is reducing this challenge [35] [36]. Aenometers on the turbines suffer from turbulence and disturbance of the wind flow from the blades and nacelle. Aenometers at multiple heights on dedicated towers can be costly and aenometers at ground level require extrapolation of the wind speed profile [37]. Despite variance of hub heights and topological features, real-time measurements of wind power production data are reasonable reflections of the wind characteristics from which the propagation of meteorological conditions through space and time to another wind power plant can be inferred [32] [31] [21].

The first approaches to capture spatio-temporal aspects showed significant improvement over persistence benchmarks but often relied upon expert knowledge of local meteorological conditions to choose the predictors from geographically dispersed sites. Larson and Westrick (2006) [38] and Gneiting et al. (2006) [39] examine forecasting a potential site located at the exit to the Columbia River Gorge using upstream meteorological observations from the entrance of the Gorge. Damousis et al. (2004) [40] utilize information available upstream under prevailing wind conditions for the Thessaloniki area. Hering and Genton (2010) [41] continued the previous studios near the Columbia River Gorge proposing trigonometric direction diurnal model and bivariate skew-t model statistical models. For these approaches to be extended to areas with more complex topology or to larger areas would require more generalised models without requiring significant expertise for identifying suitable model structures and estimation of the parameters.

Wind power and wind power forecast error fields propagate in space and in time depending on meteorological and geographic aspects, timing, and wind farm characteristics. The wind power and wind power forecast errors of wind farms in a given region is cross-correlated at significant values up to several hours and several hundred kilometres apart [42] [43]. Von Bremen et al. (2010) as reported in [10] found the forecast error cross-correlation diminishes faster over land than over sea due to the difference between offshore and onshore wind conditions. Tastu et al.(2011) [42] propose a generalized model and showed that the historical spatial and temporal propagation of wind power forecast error fields over a set of wind farms can significantly improve forecast skill. The recent wind power or forecast errors as they evolve in real time for each wind farm together with meteorological forecast conditions are inputs into the model which can continuously form an updated forecast as new data becomes available.

Recent research approaches to capture spatio-temporal aspects utilise a range of machine learning approaches including artificial neural networks, gradient boosting, random fields and classical time series approaches. Artificial neural networks have thus far only received attention for spatio-temporal wind speed forecasting [44] [45] and for solar power forecasting [46]. It is not yet clear if artificial neural networks bring additional value to time series problems over classical approaches as significant expertise is required to compare the state-of-the-art of both approaches. Bessa et al. (2015) [47] examine component-wise gradient boosting within a vector autoregressive framework combining observations of solar generation through smart meters and distribution transformer controllers. Kou et al. (2013) [48] examine generate probabilistic wind power forecasts from an online sparse Bayesian model based on a warped Gaussian process including measurements from nearby wind farms and NWP data. Wytock and Kolter (2013) [49] propose a sparse Gaussian conditional random field fitted with a second-order active set method. The main weakness of this work is a significant computational expense of 160 minutes for a case study using seven wind farms. Lenzi et al. (2017) [21] recently examined Gaussian random fields to capture spatio-temporal aspects for probabilistic individual and aggregated forecasts. Lenzi et al. show that capturing spatio-temporal dependency is required to generate aggregated probabilistic forecasts that are calibrated, as is also shown by Tastu et al. (2015) [20], who propose a Gaussian copula function to capture the underlying spatio-temporal dependencies. To reduce the computational expense, Tastu et al. (2015) utilise sparse precision matrices, and Lenzi et al. (2017) translate the data using knot-based linear combinations from a resolution of 15 minutes to 3 hours. Lenzi et al. (2017) do not indicate the loss in predictive skill from the use of knots, if any. Despite these efforts to reduce computational expense, both approaches are computationally expensive.

Classical time series analysis has been the most popular approach in recent research of spatio-temporal aspects for wind power forecasting, which can be attributed to the clear interpretation of the approach. Tastu et al. (2010) [34] expand on the autoregressive model proposed in [42] to a vector autoregressive model, which is extended to a probabilistic framework under a parametric approach employing a truncated multivariate Normal distribution. The vector autoregressive model shows significant predictive performance gains when made conditional to the average wind direction and average wind speed. Tastu and Pinson (2014) [50] further examine spatio-temporal aspects for conditional vector autoregressive models extended to a probabilistic framework. Both parametric and non-parametric approaches are examined and a non-parametric approach using adaptive quantile regression with the conditional vector autoregressive model as input had superior predictive performance compared to a state-of-the-art benchmark based on local information only.

He et al. (2014) [51] propose a model using Markov chains that include the ramp trend information and spatio-temporal dependencies to generate aggregated point and probabilistic forecasts. He et al. (2015) [52] propose a vector autoregressive model conditional to wind direction and speed fit with sparsity-constrained maximum likelihood. In both papers, the authors examine the aggregate forecasts for a single 300.5 MW wind farm for a lead time of 10 minutes and with an input data temporal resolution of 10 minutes. A significant limitation of this study is that the spatio-temporal dependencies on a relatively small spatial scale (5 x 5 km) of a single wind farm is unlikely to be well captured by 10 minute averaged power data, leading to a mismatch between spatial and temporal resolutions. If one considers on this scale that the meteorological processes propagate through space at the wind speed, then for wind speeds over 30 km/h the spatio-temporal dependencies will only partially be captured with the given temporal resolution. A smaller temporal resolution input would likely improve the results significantly.

Dowell and Pinson (2016) [32] propose a logit-normal distribution with a mean estimated by a vector autoregressive model and a variance given by exponential smoothing for each site independently. They achieve fitting computation times of approximately 20 minutes with the proposed sparsity halving the required time to fit the model. The model is tested for 22 wind farms spanning some 1800 km across South Australia, Victoria, Tasmania and the Australian Capital Territory. The methods of Dowell and Pinson (2016) suffer from mismatch of spatial and temporal scales as in He et al. [51] [52], but in this case the spatial resolution is severely excessive for the 5 minute temporal resolution of the data. This can mismatch is seen in the overly sparse parameter matrix with only wind farms within approximately 40 km of each other showing significant cross-correlation. With an order of 3, only the last 15 minutes of recently observed wind power data is used to forecast the next lead time. Meteorological systems and related wind conditions cannot propagate 1800 km in 20 minutes. Significant computation performance gains would be achieved if wind-farms outside a certain threshold distance were simply separated into separate formulations.

Cavalcante et al. (2017) [31] propose various sparse structures for a vector autoregressive model using a least absolute shrinkage and selection operator framework. The alternating direction method of multipliers is applied to fit the various least absolute shrinkage and selection operator models taking advantage of parallel computing and rapid convergence. They achieve good computational performance with time required to fit the model on the order of seconds for the case study with hourly data for 66 wind farms located in the same control area. Their model outperformed autoregressive and vector autoregressive model benchmarks, as well as the sparse vector autoregressive model from Dowell and Pinson [32]. Cavalcante et al. (2017) stress that their proposed approach can be extended to include features of other methods in the research such as using the model for spatiotemporal correction of forecast errors, making the model conditional to weather conditions, or generating probabilistic forecasts based on the logit-normal distribution.

3. Methodology

The methodology introduced here builds from wind power forecasting models based on local information only to a spatio-temporal model. Aspects of the final proposed model are inspired by elements of the spatio-temporal model proposed by Tastu et al. (2010) [34]. The proposed model aims to incorporate upstream online production information from all wind farms within a given region conditional to the meteorological conditions to improve the forecasts. The introduced models made conditional to the meteorological conditions through regimes. The regimes are based on k-means clustering of meteorological variables from NWP models aiming to characterize distinct weather regimes under which the spatio-temporal aspects, as introduced in Section 3.2.4.

To the best of the authors knowledge such regime switching modes characterizing distinct weather regimes for wind power forecasting together with spatio-temporal time series models has not yet been explored. Very recently a similar spatio-temporal forecast framework for very-short-term wind speed forecasting was published by Browell et al. (2017) [53]. They propose regimes based on an atmospheric classification of wind and pressure fields at the surface level, and the geopotential height field at the 500 hPa level extracted from the MERRA-2 reanalysis dataset with an hourly temporal resolution over the UK. To be implemented and run operationally, their method would need to be adapted to determine the atmospheric mode from the analysis of forecasts provided by a Numerical Weather Prediction (NWP) model rather than from a historical reanalysis data set. Their paper eloquently introduces the framework for spatio-temporal forecasting with clear notation and serves as inspiration to the layout and notation of the methodology introduced here.

All models introduced here were implemented into an existing wind power forecasting model developed by Vitec Software AB, called Aiolos. The Aiolos wind power forecasting model is widely used in Northern and Western Europe, and is based on Numerical Weather Prediction (NWP) models and adaptive statistical machine learning algorithms. Further information on Aiolos Forecast Model is in Section 3.3.2. The forecasting models were developed in Microsoft's Visual Studio Enterprise 2016 and implemented in the .NET framework in the programming languages C# and VB.NET. The implementation is further discussed in Section 3.3.1. The presented models were fit using ordinary least squares as discussed in Section 3.2.7. A case study was run as discussed in Section 3.1.

3.1. Case Study

3.1.1. Input Data

The wind power forecasting models proposed herein are tested on hourly wind power measurements and hourly historical numerical weather prediction (NWP) model meteorological outputs data for 24 wind farms, 23 of which are in Sweden and 1 of which is in Finland. The approximate location of the 24 wind farms is shown below in Figure 1. The 22 southern wind farms of the 24 span an area of approximately 300 km x 300 km. This geographic spread matched with hourly resolution data is deemed by the author as a suitable spatio-temporal scale match; however, higher temporal resolution data may increase the benefits of the consideration of spatio-temporal information for the wind farms that are in closer proximity. The hourly wind power measurements are the power averaged over each hour, with the units of MWh per hour. The utilised NWP model meteorological outputs include pressure at sea level, temperature, wind speed at at height of 80 meters, and wind direction. The NWP model meteorological outputs were taken from the historical predictions from SMHI's HARMONIE-AROME for each of the 24 wind farm locations.

The wind power forecasting models proposed herein are fit to historical data from January 1st to December 31st 2015 for the 24 wind farms. Forecasts were then generated for each of the proposed models from 1 hour ahead to 36 hours ahead for January 1st through to December 31st 2016 and evaluated against historical data from that year. The author emphasises the importance of splitting the data set into separate fitting and evaluation sets. All of the proposed models are then compared, including the selection of orders and regime combinations, through the generation and evaluation of a total 12.1 billion out-of-sample point forecasts.

Evaluation of the forecast has been conducted using mean absolute error (MAE) and root mean squared error (RMSE) as they are the most common performance measures for point forecasts [16]. MAE gives the same weight to all errors, while the RMSE penalizes variance as it gives errors with larger absolute values more weight than errors with smaller absolute values. The two measures together provide information for expected balancing costs and some insight of the distribution of errors [25]. The total installed capacity of the 24 wind farms is 329 MW and the capacity factor is 0.298. Normalising the MAE and RMSE to the mean production would lead to error scores given by 1 / 0.298 = 3.36 times higher than scores normalised by the installed

Figure 1: Location of the 24 Wind Farms Examined in the Case Study

capacity.

3.2. Forecast Models

3.2.1. Autoregression

First consider the problem of predicting the wind power for a single wind farm based on local information. The wind power measured at time t is contained in the time series $Y = \{y_1, y_2, \ldots, y_T\}$. The wind power forecasting framework that follows aims to calculate at time t the predicted wind power $\hat{y}_{t+\tau}$, where τ is the lead time, by solving for some function $f_\tau(\cdot)$ which maps a vector of explanatory variables onto $\hat{y}_{t+\tau}$, expressed as,

$$\hat{y}_{t+\tau|t} = f_\tau(\mathbf{x}_t)\,. \tag{1}$$

The function is solved by minimising some function of the forecast error, which is given by

$$e_{t+\tau} = \hat{y}_{t+\tau|t} - y_{t+\tau} \,. \tag{2}$$

Wind power time series are serially correlated in time. The autocorrelations of wind power from the 24 wind farms that are examined in the case study are shown below in Figure 2.

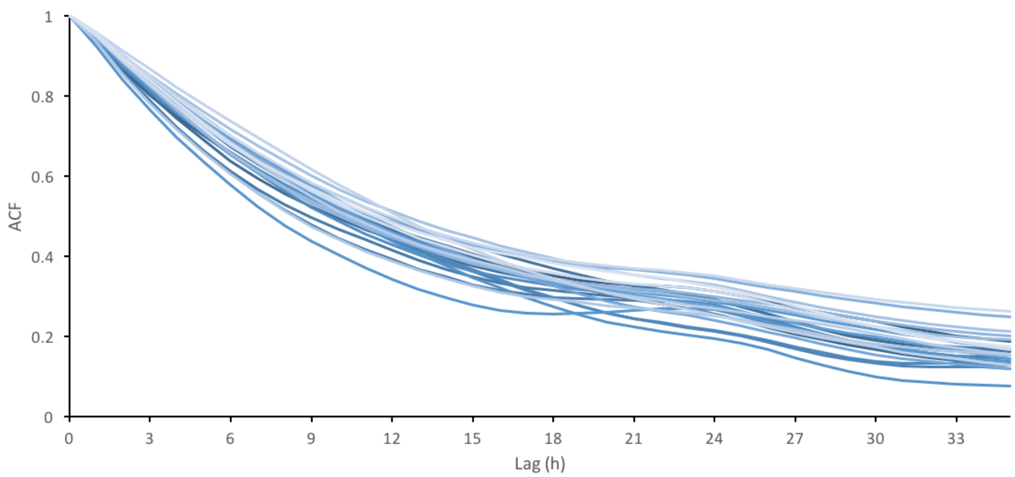

Figure 2: Autocorrelation of wind power series from 24 wind farms.

It is thus reasonable for the recent past wind power values in Y to be in the vector of explanatory variables,

$$\hat{y}_{t+\tau} = f_\tau(y_1, y_2, \ldots, y_T) \,, \tag{3}$$

and for the function $f_\tau(\cdot)$ to be the weighted sum of p past values plus a constant c_τ, forming the familiar autoregressive model of order p,

$$\hat{y}_{t+\tau} = c_\tau + \sum_{i=0}^{p-1} a_{i,\tau} y_{t-i} \,. \tag{4}$$

The selection of the order p of the model and the estimation of the parameters c_τ, $a_{i,\tau}$ for $i = 0, \ldots, p-1$ will be introduced shortly in Section 3.2.7.

3.2.2. NWP Residual Models

Two additional models based on local information only are described. Forecast error of the Aiolos wind power forecast model, as discussed in Section 3.3.2, based only on NWP information are also serially correlated in time, but to a weaker extent. The mean of the autocorrelation function of wind power and NWP only Aiolos model forecast error from the 24 wind farms are shown below in Figure 3.

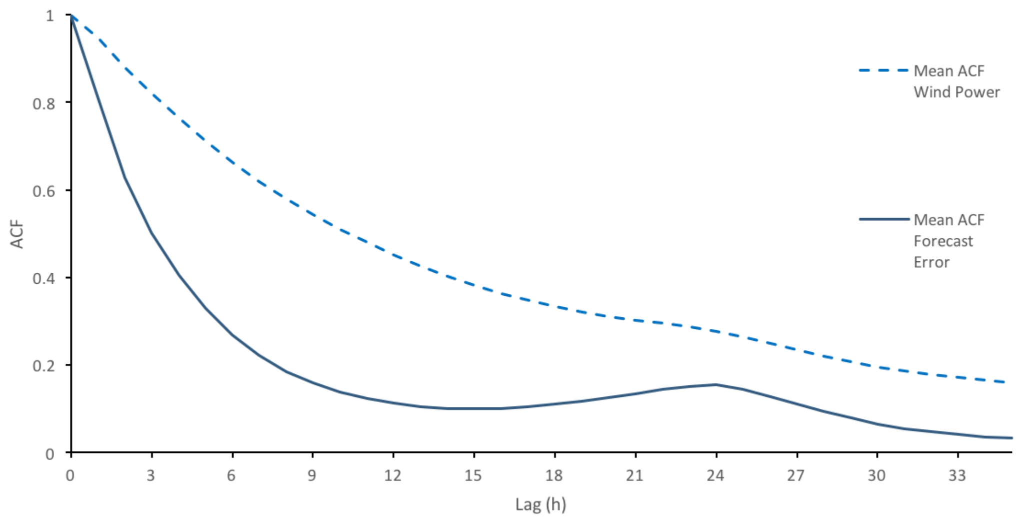

Figure 3: Autocorrelation function (ACF) of wind power series and forecast error series averaged over 24 wind farms.

As discussed earlier, wind power forecast models with NWP wind speed inputs are outperformed by purely statistical based forecasts in the first few hours ahead [10]. Despite expected weaker predictive performance, it is still reasonable to propose an autoregressive model of the p recent past NWP based model forecast error values contained in the time series $W = \{w_1, w_2, \ldots, w_T\}$ as explanatory variables, forming an autoregressive model of order p,

$$\hat{w}_{t+\tau} = c_\tau + \sum_{i=0}^{p-1} a_{i,\tau} w_{t-i} \,. \tag{5}$$

The predicted wind power $\hat{y}_{t+\tau}$ can then calculated by subtracting the predicted forecast error $\hat{w}_{t+h}$ from the original forecast $\hat{q}_{t+h}$, written

$$\hat{y}_{t+\tau} = \hat{q}_{t+\tau} - \hat{w}_{t+\tau} \, . \tag{6}$$

The Aiolos wind power forecast model with real time information is based on a similar model that is a linearly fading moving average of the p recent past NWP based model forecast error values contained in the time series $W = \{w_1, w_2, \ldots, w_T\}$. The selection of the order p of the Aiolos model determines the parameters $a_{i,\tau}$ to linearly fade from 1 to 0 for each order $i = 0, \ldots, p-1$.

3.2.3. Vector Autoregression

The interdependency among lagged wind power generation for spatially dispersed sites can be captured by extending the autoregressive time series models to vector autoregressive models, as discussed in detail earlier in Section 2.5.

The cross-correlation of wind power at wind farm 5 with each of the other wind farms in the examined set of wind farms in the case study is shown below in Figure 4. A positive cross-correlation with a given series at a negative lag indicates that the respective series contains information that can be used to improve the forecasts. The cross-correlation function of a series with itself is its autocorrelation function, and is included in Figure 4 as the red dotted curve. It is interesting to note that the cross-correlation between a lag of 4 and 12 hours with several of the wind farms is stronger than the auto-correlation information at those respective lags. The weakest cross-correlation curves are for the two wind farm sites that are much further away, with one in Western Finland and the other in Northern Sweden as shown earlier in Figure 1.

Wind power measurements made at time t and N wind farms are embedded in the vector $\mathbf{y}_t \in \mathbb{R}^N$. The vector-valued time series $\mathbf{Y} = \{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_T\}$ enables a simple representation of a vector autoregressive process of order p, expressed as

$$\hat{\mathbf{y}}_{t+\tau} = \mathbf{C}_\tau + \sum_{i=0}^{p-1} \mathbf{A}_{i,\tau} \mathbf{y}_{t-i} \, , \tag{7}$$

where $\mathbf{A}_{i,\tau} \in \mathbb{R}^{N \times N}$ are matrices of parameters and $\mathbf{C}_\tau \in \mathbb{R}^N$ are vectors of constants. Unique parameter matrices are fit for each lead time τ. The parameter matrix is displayed for clarity as

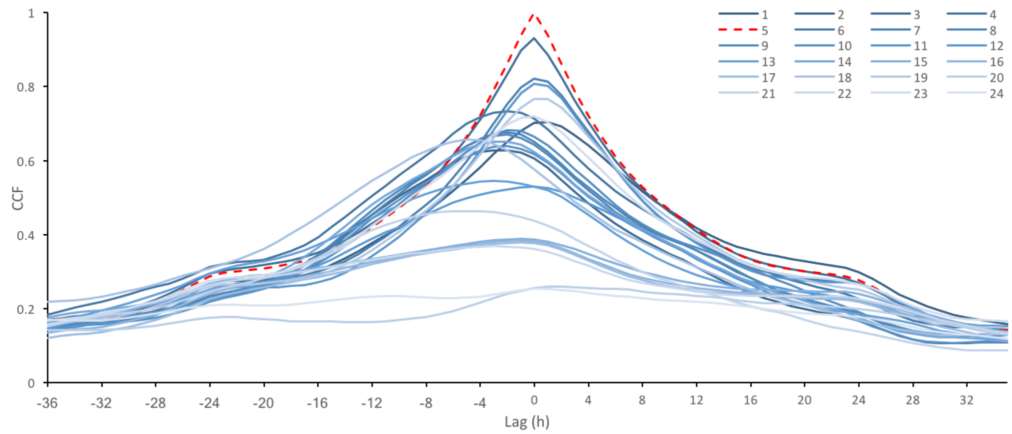

Figure 4: Cross-correlation function (CCF) of wind power series between wind farm 5 and 23 other wind farms.

$$\mathbf{A}_{i,\tau} = \begin{bmatrix} a_{i,\tau}^{11} & a_{i,\tau}^{12} & \dots & a_{i,\tau}^{1N} \\ a_{i,\tau}^{21} & a_{i,\tau}^{22} & \dots & a_{i,\tau}^{2N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{i,\tau}^{N1} & a_{i,\tau}^{N2} & \dots & a_{i,\tau}^{NN} \end{bmatrix}. \tag{8}$$

The parameters on the diagonal of $\mathbf{A}_{i,\tau}$ give the autocorrelation effects and the off-diagonal parameters give cross-correlation between each of the wind farms. In other words, each wind farm power series not only now has predictors given by the lagged values of its own series, but the lagged values of all of the other wind farms in the set. The input vector of wind power measurements of size N is given by

$$\mathbf{y}_{t-i} = \begin{bmatrix} y_{t-i}^{1} \\ y_{t-i}^{2} \\ \vdots \\ y_{t-i}^{N} \end{bmatrix}. \tag{9}$$

The target vector of wind power measurements of size N is given by

$$\hat{\mathbf{y}}_{t+\tau} = \begin{bmatrix} \hat{y}^1_{t+\tau} \\ \hat{y}^2_{t+\tau} \\ \vdots \\ \hat{y}^N_{t+\tau} \end{bmatrix}. \tag{10}$$

The vector of constants of size N is given by

$$\mathbf{C}_\tau = \begin{bmatrix} c^1_\tau \\ c^2_\tau \\ \vdots \\ c^N_\tau \end{bmatrix}. \tag{11}$$

3.2.4. Regimes

Since wind power is a result of meteorological conditions, it is desirable to include variables in the models thus far introduced that are able to characterise the meteorological conditions. Tastu et. al (2010) [34] were able to improve the wind power predictive performance of a spatio-temporal model by making it conditional to the meteorological conditions, reducing the RMSE by between 4.08% to 18.46% at one hour ahead for groups of wind farms in Denmark over Wind Power Prediction Tool, a state-of-the-art wind power forecast model. This was achieved through conditional parametric models with a linear structure, which are similar to vector autoregressive models but for which the matrices of parameters $\mathbf{A}_{i,\tau} \in \mathbb{R}^{N\times N}$ are replaced by smooth functions. These functions were conditioned on average wind speed and direction. Their key finding of note here is that the propagation of the forecast errors was better explained by accounting for the meteorological conditions.

The meteorological conditions are to be captured here using regimes based on clustering of meteorological variables. The meteorological variables used to form the regimes include $\hat{P}$ pressure at sea level, $\hat{T}$ temperature, $\hat{WS}$ wind speed at at height of 80 meters, and $\hat{WD}$ wind direction. The data was taken from the historical predictions of these variables from SMHI's numerical weather prediction model HARMONIE-AROME for each of the 24 wind farm locations in the case study.

Two types of regimes are proposed. The first type includes individual regime modes, which are based on meteorological conditions specific to each site. The second type includes field regime modes, which are based on the mean of each of the meteorological variables across all of the sites. For the autoregressive models the regime allocation can be made for each wind farm based on the value of the meteorological variables at that location. However, for the vector autoregressive models, the regime allocation in its proposed form needs to be made based on the mean of each of the meteorological variables across all sites.

The individual regime mode at time t is denoted by $m_t \in s = \{1, 2, \ldots, k\}$ and similarly, the field regime mode at time t is denoted by $M_t \in S = \{1, 2, \ldots, K\}$. Consider now auto regression and vector autoregressive models that are mode specific, and which switch regimes by the allocated regime mode for a given data point. The auto regressive model in Equation (4) becomes

$$\hat{y}_{t+\tau} = c_\tau m_t + \sum_{i=0}^{p-1} a_{i,\tau} m_t y_{t-i}\,, \tag{12}$$

and the vector autoregressive model in Equation (7) becomes

$$\hat{\mathbf{y}}_{t+\tau} = \mathbf{C}_\tau M_t + \sum_{i=0}^{p-1} \mathbf{A}_{i,\tau} M_t \mathbf{y}_{t-i}\,. \tag{13}$$

The individual regime mode m_t and field regime mode M_t are discrete and result in separate auto regressive and vector autoregressive models respectively to be fit for each regime. The parameters are estimated using only the subset of the available training data which corresponds to the respective mode.

In this spatio-temporal framework characterised by many parameters, it is beneficial to capture the propagation of these meteorological systems using a limited number of regimes despite the complex nature of the systems. The desire for a limited number of regimes is that more regimes decrease the number of samples available for parameters estimation, and insufficient training data can result in poor parameter estimates. In the atmospheric classification for regime switching vector autoregressive model for the prediction of wind speeds, Browell at al. found that 3 regimes were optimal out of the original 21 possible atmospheric regimes identified in the reanalysis data [53].

It is intended that the regime switching models developed here be general so that the models can be expanded to other countries or regions with out local meteorological expertise. K-means clustering was used to form regimes by allocating the meteorological variables, $\hat{P}$, $\hat{T}$, $\hat{WS}$, and $\hat{WD}$ into clusters. K-means clustering is a type of unsupervised learning used to find and allocate groups in a given set of data. The forecast performance for each forecast model was optimised by searching for the optimal number of regimes, given by k for individual regimes and K for field regimes, reflecting here the number of clusters to be considered. Each of the considered meteorological variables was normalised using Gaussian normalization. The K-means algorithm is initialised with allocation to a randomly selected cluster. In the first step, the means of the clusters, or centroids, are calculated and updated. In the next step, each data point q_t is assigned to its nearest centroid m_i, by the squared Euclidean distance, given by

$$\arg\min_{m_i \in M} \sqrt{\sum_{i=1}^{n} (q_t - m_i)^2}.$$

The algorithm is then looped through these two steps until there is no change in the clustering or the maximum number of iterations constraint is met. The clustering results of the K-means algorithm may be a local optimum and not a global optimum.

The scatter plots of each of these meteorological variable forecasts is shown below with respect to the measured wind power for a given wind farm in Figure 5. The relation between the wind speed forecast at a given location and the measured wind power reflects the familiar wind power curve, and the large variability of the measured wind power for a given wind speed forecast is a reminder of the challenging and stochastic nature of wind power forecasting. While the relations between wind power and the remaining three meteorological variable forecasts of pressure, temperature and wind direction are weaker, each of the meteorological variables has potential to provide further information to inform the allocation of the regime, and to better describe the spatio-temporal propagation of the meteorological conditions.

The result of one of the K-means clustering algorithm runs showing the clustered groups with field wind speed and field temperature as the selected meteorological variables is shown below for illustration in Figure 6.

All possible combinations of the 4 meteorological variables are considered and tested as potential sets of explanatory variables for allocation of the

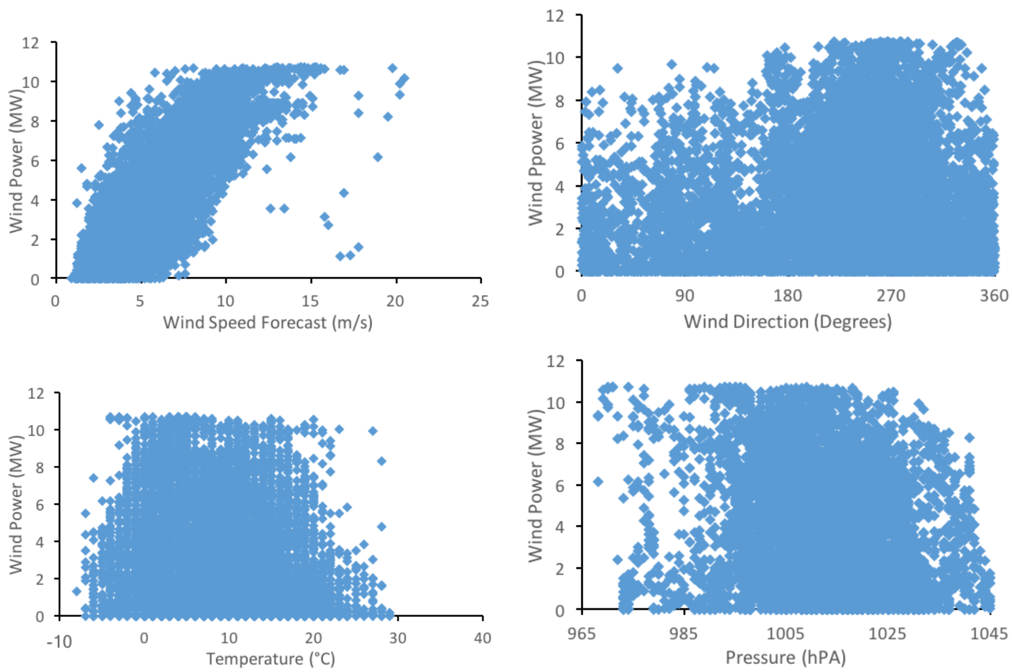

Figure 5: Plots of measured wind power at one wind farm over a year against forecasts for wind speed, wind direction, temperature and pressure.

meteorological regime. The intuitive logic behind testing all possible combinations of the meteorological variables is that pressure, temperature, wind speed and wind direction can each provide additional information to better characterize a given regime. It can be conjectured that low pressure events will on average be associated with certain wind processes. If pressure is then considered together with wind speed and wind direction information can further characterise the low pressure event. If pressure, wind speed and wind direction are then considered together with temperature it may better capture potential convection processes. Ultimately the underlying processes that define the meteorological regimes do not need to be known, the hypothesis is merely that clustering these meteorological variables together can better characterize the meteorological processes and their evolution than considering them individually. The optimal combination of meteorological variables and the optimal number of clusters are selected for each model proposed herein by examining the improvements in predictive skill of each of the respective

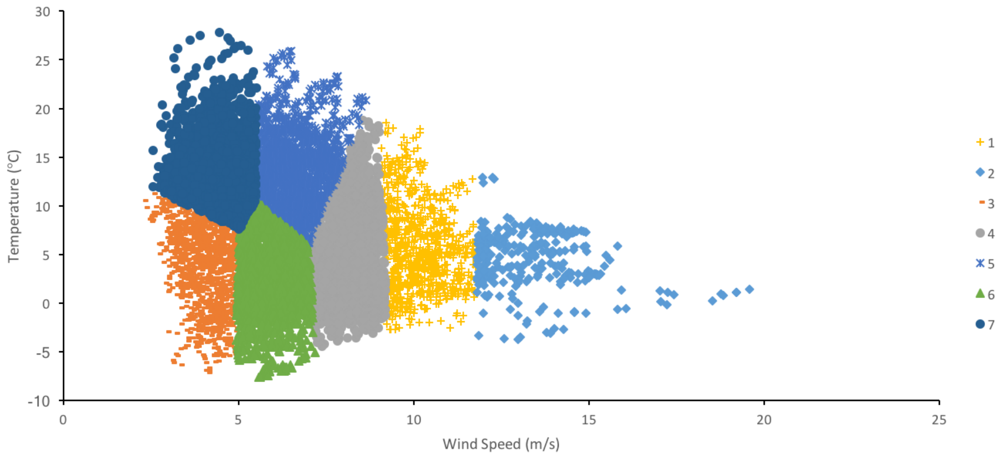

Figure 6: K-means Clustered Groups with Field Wind Speed and Field Temperature as Selected Meteorological Variables

models.

3.2.5. Two-step Regime Switching Model

Recall that two types of regimes are proposed, the first type includes the individual regime modes and the second type includes the field regime modes. It is conjectured that it is beneficial to consider both types in a single model. The individual regime modes capture meteorological processes specific to each location, and the field regime modes capture the propagation of meteorological processes from one site to another. For this reason, a two step model is proposed. In the first step a regime switching autoregressive model as proposed in Equation (12), with regimes based on location specific meteorological variables, is used to generate forecasts. In the second step, a regime switching spatio-temporal vector autoregressive model is proposed to capture the spatio-temporal propagation of the forecast errors of the regime switching autoregressive model from the first step, with regimes based on the mean of each of the meteorological variables across all sites.

Consider the p recent past forecast error series $R = \{r_1, r_2, \dots, r_T\}$ of wind power forecasts made with the proposed regime switching autoregressive model, as given in Equation (12). These forecast errors can be set as explanatory variables, forming a vector autoregressive model of order p,

$$\hat{\mathbf{r}}_{t+\tau} = \mathbf{C}_{\tau} + \sum_{i=0}^{p-1} \mathbf{A}_{i,\tau} M_t \mathbf{r}_{t-i} \,, \tag{14}$$

Similar to Equation (6), the final predicted wind power vectors, for clarity, denoted $\hat{\mathbf{F}}_{t+h}$, can then formed by adding the predicted forecast error vectors $\hat{\mathbf{r}}_{t+h}$ to the vector of original regime switching autoregressive model forecast vectors $\hat{\mathbf{y}}_{t+h}$. Forming a model expressed as

$$\hat{\mathbf{F}}_{t+\tau} = \hat{\mathbf{r}}_{t+\tau} + \hat{\mathbf{y}}_{t+\tau} \,. \tag{15}$$

This approach allows for the information from the meteorological regimes at each individual location to corrected independently under individual regimes before considering the spatio-temporal dependencies under a regime characterized by the mean meteorological conditions across all locations.

3.2.6. Seasonality

Wind power time series exhibit exhibit diurnal seasonality due to the underlying diurnal seasonality of wind speeds and meteorological conditions. This can be observed by the slight increase in autocorrelation and cross-correlation values at a lag of 24 hours in Figure 2 and Figure 4 respectively. A simple way of characterising any additional remaining part of the underlying meteorological conditions not already captured in the previously introduced regimes is therefore is to include the time of day exogenously. This can be achieved by including a boolean function $d_h(t)$ of a set of variables $h \in H$ where H is determined by the temporal resolution and is the number of discrete measurements in a day. For the case of hourly data, h is the time of the day, $H = \{0, 1, \ldots, 23]$, t_h is the time of day of the associated value in the time series at time t, and

$$d_h(t) = \begin{cases} 1 & \text{for } t_h = h \\ 0 & \text{for } t_h \neq h \end{cases} \,. \tag{16}$$

The intercept c_τ of the regime switching auto regressive model given in Equation (12) is then replaced by $b_{h,\tau}$ reflecting time dependent intercepts, and the regime switching autoregressive model with exogenous diurnal variables, is given by

$$\hat{y}_{t+\tau} = \sum_{i=0}^{p-1} a_{i,\tau} m_t y_{t-i} + \sum_{h \in H} b_{h,\tau} m_t d_h(t+\tau)\,. \tag{17}$$

A similar extension can be made for the other vector autoregressive models, take the regime switching vector autoregressive model as an example, as presented in Equation (13), where the vector of constants $\mathbf{C}_\tau \in \mathbb{R}^N$ is then replaced by $\mathbf{B}_{h,\tau} \in \mathbb{R}^N$ reflecting a vector of time dependent intercepts, and the set of diurnal variables is replaced by a vector of diurnal variables $\mathbf{B}_{h,\tau} \in \mathbb{R}^N$. The regime switching vector autoregressive model with exogenous diurnal variables, can then be expressed as

$$\hat{\mathbf{y}}_{t+\tau} = \sum_{i=0}^{p-1} \mathbf{A}_{i,\tau} M_t \mathbf{y}_{t-i} + \sum_{h \in H} \mathbf{B}_{h,\tau} M_t \mathbf{d}_h(t+\tau)\,, \tag{18}$$

where $\mathbf{A}_{i,\tau} \in \mathbb{R}^{N \times N}$ are matrices of parameters.

3.2.7. Parameter Estimation

The model parameters $\boldsymbol{\beta}_{\tau,s} = \begin{bmatrix} \mathbf{A}_{0,\tau,s} & \dots & \mathbf{A}_{p-1,\tau,s} & \mathbf{B}_{0,\tau,s} & \dots & \mathbf{B}_{23,\tau,s} \end{bmatrix}$ can be estimated by minimising some function of the forecast errors given a historical dataset. A unique set of parameters is fit for each lead time independently.

For $1 \leq t \leq T - \tau$ of wind power measurements with regime mode s and associated diurnal variables the matrix of input data of size $(pN + 24) \times T$, is given by a horizontal concatenation of explanatory variables, expressed as

$$\mathbf{X}_{\tau,s} = \begin{bmatrix} \dots & y_t^1 & \dots \\ \dots & y_t^2 & \dots \\ & \vdots & \\ \dots & y_t^N & \dots \\ & \vdots & \\ \dots & y_{t-p-1}^N & \dots \\ \dots & d_0(t+\tau) & \dots \\ & \vdots & \\ \dots & d_{23}(t+\tau) & \dots \end{bmatrix}. \tag{19}$$

The corresponding target matrix of wind power measurements for $p + \tau \leq t \leq T$ of size $N \times (T - p - \tau)$ is given by horizontal concatenation of the target vectors

$$\mathbf{Y}_{\tau,s} = \begin{bmatrix} \cdots & \hat{y}_t^1 & \cdots \\ \cdots & \hat{y}_t^2 & \cdots \\ & \vdots & \\ \cdots & \hat{y}_t^N & \cdots \end{bmatrix} . \tag{20}$$

The above parameter matrices, input matrices and target matrices are described for the full regime switching vector autoregressive model with diurnal seasonality. The respective matrices for the other proposed models are formed by removing the non-relevant elements, for example the regime switching vector autoregressive model without diurnal seasonality would not contain the related diurnal variables and parameters.

The sum of the squared error is chosen here as the cost function for all of the proposed models, known as ordinary least squares, with the parameters estimates given by the solution to

$$\arg\min_{\boldsymbol{\beta}_{i,\tau}} \parallel \mathbf{E}_{\tau,s} \parallel_2^2 = \arg\min_{\boldsymbol{\beta}_{i,\tau}} \parallel \mathbf{Y}_{\tau,s} - \boldsymbol{\beta}_{\tau,s}\mathbf{X}_{\tau,s} \parallel_2^2 \ . \tag{21}$$

The ordinary least squares estimator may be eloquently expressed as

$$\boldsymbol{\beta}_{\tau,s} = (\mathbf{X}_{\tau,s}^{'}\mathbf{X}_{\tau,s})^{-1}\mathbf{X}_{\tau,s}^{'}\mathbf{Y}_{\tau,s} \, . \tag{22}$$

This cost function can be extended by introducing regularisation to constrain resulting solution potentially enabling better generalisation [54]. Regularsation induces sparsity into the parameter matrix, mitigating the potential weakness of ordinary least sqaures to overfit problems in high parameter spaces [55]. The least absolute shrinkage and selection operator or ridge regression are common penalty parameters for regularisation methods [54]. The model can also be extended to utilise parallism and more rapid convergence can by solving the problem with alternating direction method of multipliers as proposed by Calvalcante et al. (2017) [31]. It is conjectured regularisation and parallelism are not required for the relatively small case study of hourly resolution for 24 wind farms and thus are not studied here, they are prudent future extensions for the consideration of significantly larger data sets with smaller time resolution and more wind farms as the fitting problem grows with the square of the number of wind farms considered, increasing difficulty of fitting the problem and computation expense. This conclusion is supported by the recent works of Browell et al. (2017) [53] which produced promising wind speed forecast improvement for 23 sites using a regime switching vector autoregressive model without employing regularisation.

3.3. Implementation

3.3.1. Software Development

The proposed wind power forecasting models were developed in Microsoft's Visual Studio Enterprise 2016 and implemented in Vitec's .NET framework in the programming languages C# and VB.NET. Microsoft Visual Studio is an integrated development environment and its source code editor, build automation tools and debugger were used to build the proposed models. There are several reasons for this integrated development environment choice over developing the model in another other environments or language such as R or MATLAB. It was intended from the beginning that this thesis make a significant contribution to the currently implemented wind power forecasting in industry. Aiolos forecasting studio is implemented in the .NET framework and so implementing the new model in the .NET framework allows the model to be implemented with ease into the existing Aiolos Forecast Studio.

As discussed in Section 2.3, incorporating spatio-temporal aspects can be computationally expensive, and writing and developing the model in the chosen level of abstraction language allows for good computational performance to be obtained. The implementation of the model in terms of its computational efficiency is an important focus as it is closely linked to the overall effectiveness of the model. In the case one or more measured wind power data series are not usable, due to the data being unavailable or due to planned downtime, it can not be included in the spatio-temporal model and the model becomes incomplete. It is practical to give the end user the ability to rapidly refit the model excluding the wind farm series with issues, and to generate spatio-temporal forecasts for the other wind farms without issue. The wind farm series with issues can then have forecasts generated independently of the other wind farms. As such issues happen regularly in practice, it is conjectured that the proposed regime switching vector autoregressive model will be fit multiple times per week even even though the model parameters will only drift slowly with time if fit to a reasonable amount of historical data.

Minor preprocessing of data is achieved through a script that skips missing data and records the counts. The data for all wind farms have less than 1% of missing data for the presented case study and can be considered of very good quality. As discussed earlier, scripts were developed for future cases where series may need to removed from the spatio-temporal models due to missing data and allocated for forecasts based on local information only. A simple post processing script checks that all forecasts were within the bounds of 0 and the installed capacity of the wind farm.

All development and testing was performed in Microsoft's Visual Studio Enterprise 2016 on a laptop running 64 bit Windows 10 Enterprise with an Intel Core i7-4600U CPU @ 2.1 GHz processor, and 8.00 GB of RAM. For the presented case study, all models proposed herein achieved reading of data and fitting times below 30 seconds apart from the two step model which took up to 1 minute. The two step model involved generating forecasts based on locational information before making spatio-temporal corrections as presented in Section 3.2.5. A year of point forecasts can be generated in less than 2 seconds, and evaluated for the purpose of this thesis also in less than 2 seconds. Better model performance can be achieved with small extensions to the proposed models by introducing regularisation and by using fitting algorithms that can take advantage of parallelism and more rapid convergence such as in the models proposed by Calvalcante et al. (2017) [31].

3.3.2. Aiolos Forecast Model

This Master thesis has been written in collaboration with the Energy group of Vitec Software AB. Vitec is a leading developer and supplier of Energy software on the Northern European market with approximately 170 customers, providing software for companies including E.ON, Fingrid, Svenska Kraftnat, Fortum, Helsinki Energy, and Vattenfall. The Aiolos wind power forecasting model is part of Vitec's software-as-a-service Aiolos Forecasting Studio which provides forecasts of electricity load, heat load, run of river hydro production, solar power production, and wind power production. Users of Aiolos Forecasting Studio include transmission system operators, distribution system operators, power producers, retailers, and traders.

An introduction to the Aiolos forecasting model follows. Aiolos wind power forecasting model utilises an ensemble of numerical weather predictions

(NWP) from the weather forecast providers they cooperate with which varies depending on the region under consideration. Most of the NWP providers includes weather parameters for the next 72 hours at half hourly or hourly resolutions. Longer resolution NWP parameter predictions are typical of time horizons beyond three days and up to ten days into the future. The key weather parameters from NWP include wind speed, wind direction, pressure, temperature, and pressure all of which are provided at various heights from 10 m to 800 m above sea level. The latitude and longitude of each wind power plant are used to interpolate NWP meso-scale forecast to better capture the site specific wind conditions. The benefit of this interpolation is that wind farms near the edge of grid boundaries can incorporate forecasts from the neighbouring boundary. The vertical wind profile is estimated based on both NWP wind speeds at various heights, pressure, and temperature. The wind speed is vertically interpolated to the hub height of each wind power plant. A model based on a trimmed non-linear regression between the historical power production and weather forecasts is then fit. The model is made conditional to the wind direction using regimes. The number of wind direction regimes is optimised based on an evaluation of performance against historical data. If historical data is not available, adjusted power curves are used. Wind power forecasts are then estimated for each available NWP provider and various ensembles of those NWP models to form preliminary production forecasts. Depending on performance of each preliminary production forecast for each wind farm, an optimised weighting of available NWP ensembles is formed for the final forecast. The optimal ensemble can also change with the prediction horizon. Maintenance functionality in Aiolos Forecast Studio allows maintenance planning and and to account for scheduled maintenance in the forecast. Real-time production data is utilised to individually correct the very short term forecasts taking advantage of auto correlation of forecast errors at wind power plants. The Aiolos final wind power forecast is displayed in tables and graphs in Aiolos Forecast Studio and are available for export in a number of formats. Aiolos forecast studio allows the import of external wind power forecasts from other wind power providers which can also be weighted with the final Aiolos forecast.

The historical Aiolos model forecasts, production, and meteorological data were exported from Vitec's Aiolos Forecast Studio. Aiolos Forecast Studio export functionality to comma separated value (.csv) file types was utilised to allow the model to be run without fully integrating the model to Aiolos Forecast Studio. The full integration of the model requires integrating the functionality with the user interface which was outside of the scope of this thesis. This work will later be completed by the user interface developers at Vitec. The Aiolos model forecasts, production, and meteorological data was read from the .csv files types. Vitec has developed a custom data type within their .NET dynamic library for Aiolos Forecast Studio to allow large time series data types to be efficiently stored with other important characteristics of the underlying asset and time information allowing for ease of access to the data. This data type was used to store the read data from the .csv file and allows for the settings of the model to be both easily adjusted as well as assisting with the full implementation of the model into Aiolos Forecast Studio.

4. Results and Analysis

The results and analysis from the case study follow. All the wind power forecasting models proposed in Section 3 are tested on hourly wind power measurements and hourly historical numerical weather prediction (NWP) model meteorological outputs data for the 24 wind farms in the case study. Additionally persistence forecasts are generated for benchmarking purposes, where the forecast at some future time is given by the most recently measured wind power. The performance measures of mean absolute error normalised to the installed capacity (MAE) and root mean squared error normalised to the installed capacity (RMSE) are utilised here. For the most part all performance measures reported are the average of the individual errors, but are simply referred to at MAE and RMSE. Note it must be stressed the performance measures are not evaluated on the aggregation of the forecast errors. Aggregation of forecast errors significantly reduces the total forecast error scores [30]. The total installed capacity of the 24 wind farms is 329 MW and the capacity factor is 0.298. Normalising the MAE and RMSE to the mean production would lead to error scores given by 1 / 0.298 = 3.36 times higher than scores normalised by the installed capacity. For further detail of the case study see earlier discussion in Section 3.1.

Up to an order of 12 is considered for all of the proposed autoregressive and vector autoregressive models. For all models an order of 2 is found to be the most appropriate selection, with higher orders giving negligible improvement in predictive performance.

4.1. Base Models

The models defined as base models here are those without diurnal seasonality and without regimes conditioned by meteorological conditions. Each of the base models outperforms the persistence benchmark for MAE and RMSE scores as seen in Figure 7 and Figure 8. The poorest performing base models are those based on the errors of the Aiolos wind power forecasting model based on NWP. The Aiolos wind power forecast model with real time measurements included is based on the linearly fading moving average of the recent past NWP based model error values, denoted Fade Residual NWP. It is outperformed by the autoregressive model of the recent past NWP based model forecast error values, denoted AR Residual NWP, and given earlier in Equation 6. The poorer performance reflects excessive weight give to NWP based information which worsens the potential predictive skill for short term wind power forecasting. This result supports the common finding in the research that models with emphasis on statistical methods outperform those with emphasis on physical methods for times horizons up to 3 to 6 hours ahead [10]. Figure 3 shown earlier further explains this result, with the autocorrelation of NWP based observed forecast errors declining much faster with time compared to the autocorrelation of measure wind power.

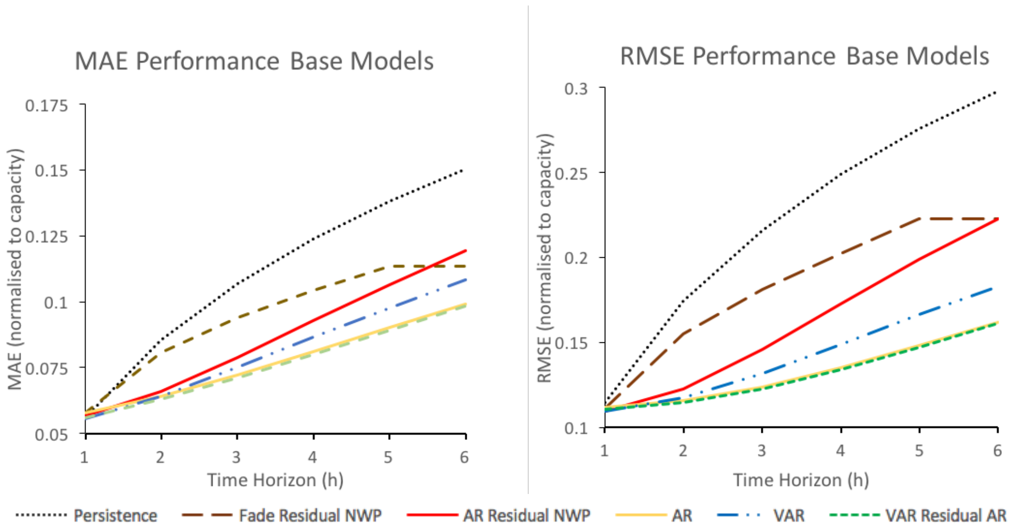

Figure 7: Mean Absolute Error (MAE) Normalised to Installed Capacity and Root Mean Squared Error (RMSE) Normalised to Installed Capacity Performance of Base Models

The base autoregressive model based on measured wind power measurements, denoted AR and given earlier in Equation (4), outperforms the base vector autoregressive model also based on measured wind power measurements beyond 2 hours ahead, denoted VAR and given earlier in Equation (7). While the VAR model outperforms AR for 1 hour ahead as expected, the result of weaker performance for 2 hours ahead and beyond was not expected as previous research on similar models indicates the consideration of spatio-temporal information to improve the prediction skill compared to to forecasts based on local information alone. A potential explanation for this result is poor fitting of the model using ordinary least squares without regularisation to induce sparsity to the parameter matrix. He et al. (2015) [52], Dowell and Pinson (2016) [32] and Cavalcante et al. (2017) [31] all utilise regularisation in the fitting of their respective models. However, He et al. (2015) Dowell and Pinson (2016) only examine the predictive performance of the first lead time. While Browell et al. (2017) [53] do not utilise regularisation, they only benchmark their vector autoregressive model to persistence and it is thus possible that it does not outperform an autoregressive model.

The weakness of not utilising regularisation in the fitting process for the VAR model is mitigated through the Two-step Model proposed in Section 3.2.5. This can be seen as the two-step model, here without regimes or diurnal components, denoted VAR Residual AR, is seen to outperform the AR model. This effectively allows all autoregressive information to be removed from the VAR fitting procedure, reducing the difficulty to achieve a good fit for the model [54].

The percentage improvement of each of the base models predictive skill compared to persistence is shown below in Figure 8. Comparing RMSE and MAE measures for 1 hour ahead, it is interesting to note that only VAR and VAR Residual AR marginally outperform persistence for the first lead in terms of MAE. In contrast, in terms of RMSE all of the base models outperform persistence for the first lead time. This indicates that each of the base models is able to reduce the larger errors more so than persistence as RMSE penalises outliers.

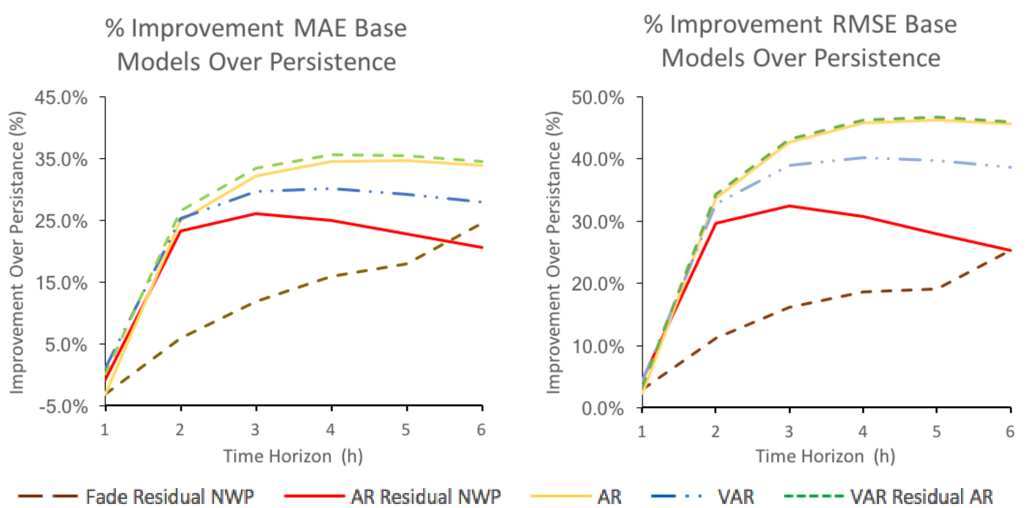

Figure 8: Mean Absolute Error (MAE) Normalised to Installed Capacity and Root Mean Squared Error (RMSE) Normalised to Installed Capacity Percentage Improvement of Base Models Over Persistence

The improvement shown for the AR, VAR, and VAR Residual AR base models compared to the Fade residual NWP model is already of significant value for Vitec's Aiolos wind power forecasting model which currently has its real time corrections based on the Fade Residual NWP model.

4.2. Regime Models

Making the autoregressive models conditional to the meteorological conditions through the proposed regimes significantly improves the predictive skill. Recall from Section 3.2.4, the meteorological conditions are captured here using regimes based on K-means clustering of the $\hat{P}$ pressure at sea level, $\hat{T}$ temperature, $\hat{WS}$ wind speed at at height of 80 meters, and $\hat{WD}$ wind direction. The optimal number of regimes specified for the K-means algorithm ranges from 3 to 16 depending on the model and meteorological variables considered. The consideration of more than 2 meteorological variables as inputs to form the regimes is found to have negligible impact on the predictive performance of all the benchmarked models. This indicates that the consideration of 3 or more of the considered meteorological variables does not provide additional information that is beneficial. This may be conjectured to be due to the noisy and interdependent nature of these variables, as can be seen in the earlier displayed plots in Figure 5. The confounded nature of these variables also can explain why each of the combinations of these variables resulted in similar improvements in forecast skill.

The various combinations of regime inputs to form the regime switching autoregressive models show similar improvements compared to the base autoregressive model as shown below in Figure 9 and Figure 10. These improvements in forecast skill align with previous research on regime switching autoregressive models from Gallego et al. (2011) [15] and from Trombe and Pinson (2012) [16].

The regimes that included forecast wind speed as an input to the K-means clustering show good performance and are only outperformed combination of pressure and temperature as inputs to the K-means clustering. The combination of temperature and pressure predictions as inputs to the K-means clustering with 7 groups was found to have the best average performance over the first 6 hours, with percentage improvement in MAE over the base autoregressive model of 3.9%, 11.1%, 18.0%, 23.7%, 28.5%, 31.9%, for each of the first 6 respective lead times. It is interesting that the combination of temperature and pressure outperforms regimes based on wind direction and wind speed. Making wind power foreacasting models conditional to wind direction and wind speed is not only the most common in research [10], they

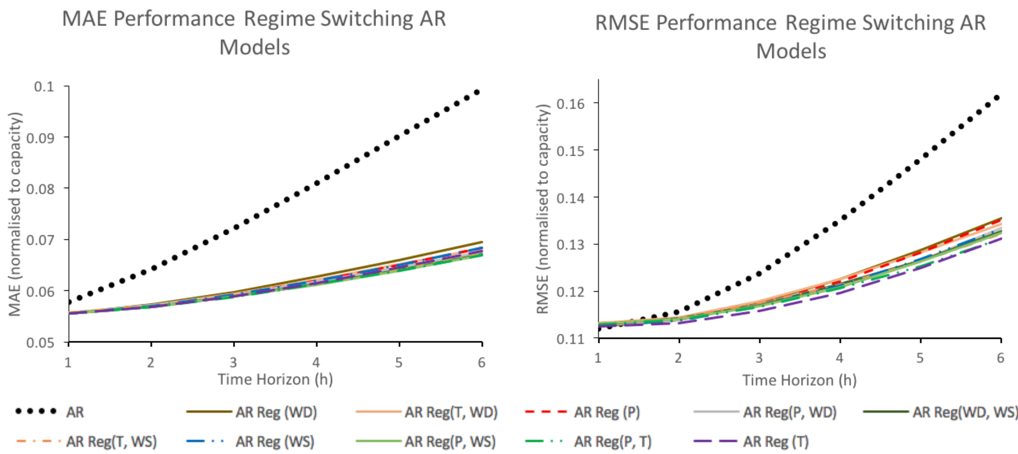

Figure 9: Mean Absolute Error (MAE) Normalised to Installed Capacity and Root Mean Squared Error (RMSE) Normalised to Installed Capacity Performance of Regime Switching Autoregressive Models

are the most logical. It is shown that pressure and temperature deserve further consideration for very short term wind power forecasting models which are made conditional to meteorological conditions.

The percentage improvement compared to the base autoregressive model increases significantly with the time horizon. Notably, each of the regime switching autoregressive models under performs the base autoregressive model by between 0 to 1% in terms of RMSE for the first hour ahead, while showing 3.6% to 4.0% improvement in terms of MAE, as shown in Figure 10

It can be asserted that making the autoregressive model conditional to the forecast meteorological conditions allows the model to better capture the local underlying meteorological processes that determine wind power generation, namely wind speed and how it evolves through time.

4.3. Diurnal Seasonality

The consideration of the diurnal seasonality extensions, as presented in Section 3.2.6, showed some improvement in predictive skill over the base models. However the addition of diurnal seasonality extensions to the regime switching autoregressive and vector autoregressive models showed negligible improvements. Browell et al. (2017) [53] reports a similar finding that the diurnal seasonality provides negligible additional benefits after the spatio-temporal model is made conditional to the meteorological conditions. It is

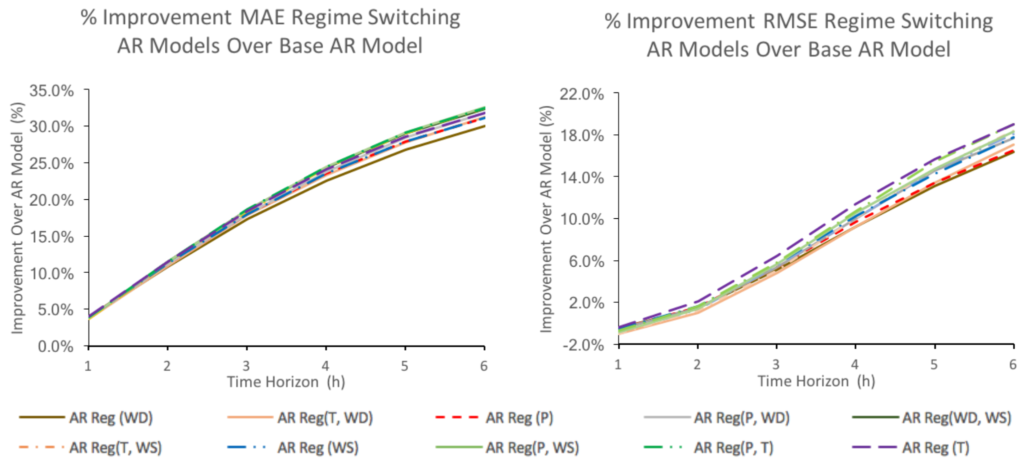

Figure 10: Mean Absolute Error (MAE) Normalised to Installed Capacity and Root Mean Squared Error (RMSE) Normalised to Installed Capacity Percentage Improvement of Regime Switching Autoregressive Models Over Base Autoregressive Model

conjectured that the diurnal seasonality is captured by the regimes based on meteorological conditions. This can be explained as the diurnal seasonality exhibited by wind power is a function of the diurnal seasonality of the underlying meteorological conditions, for example, wind speeds may be higher on average during afternoons at coastal locations due to local convection causing local sea-breezes.

4.4. Two-step model benchmark

The two-step regime switching model, as proposed in Section 3.2.5 achieved the best performance of all the proposed models. Figure 11 shows the MAE and RMSE performance of the two-step regime switching model denoted Two-step Model, the best performing regime switching autoregressive model denoted AR Reg(P,T), the base autoregressive model denoted AR, the Fade Residual NWP as currently used in the Aiolos wind power forecast model, and persistence. All of the proposed models show significant improvement over persistence and the Fade Residual NWP model of Vitec's Aiolos wind power forecasting model, especially for 2 hours head onwards. The percentage reduction in MAE of the two-step model over the regime switching autoregressive model benchmark is 4.7% for 1 hour ahead and increases to 34.1% at 6 hours ahead. The reductions in forecast error from the hour ahead to six hours equates to subtantial monetary value in terms of reduced balanacing costs for Vitec's customers [5]. Recall that the users of Aiolos Forecasting Studio include transmission system operators, distribution system operators, power producers, retailers, and traders. For transmission and distribution system operators with increasing penetration of wind power, the improved forecasts are important to the reliable and economic power system operation. The larger reduction of forecast error at several hours can be utilised by the customers for more efficient and economic optimisation, both for internal energy dispatch and externally for customers active on intra-day markets who can trade their position [5].

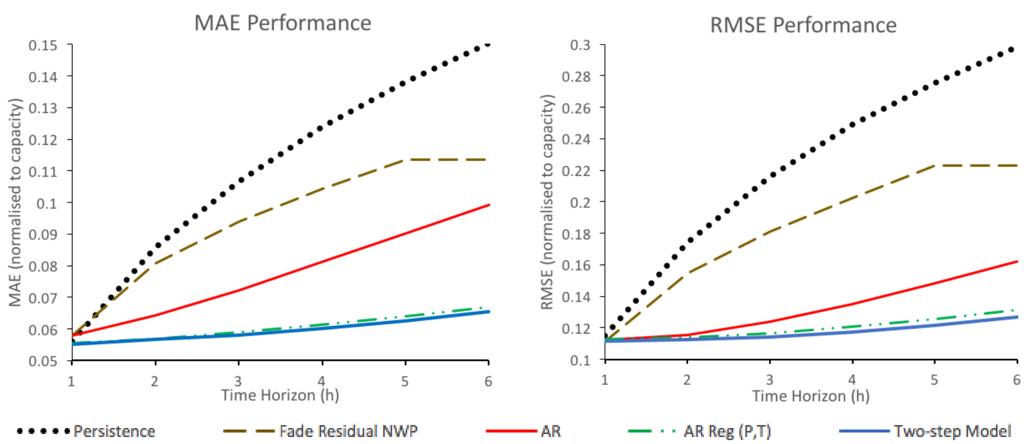

Figure 11: Mean Absolute Error (MAE) Normalised to Installed Capacity and Root Mean Squared Error (RMSE) Normalised to Installed Capacity Performance

Recall the first step of the two-step model is the generation of preliminary forecasts using a regime switching autoregressive model with regimes based on location specific meteorological variables. In the second step, the regime switching spatio-temporal vector autoregressive model captures the spatio-temporal propagation of the forecast errors of the regime switching autoregressive model from the first step, with regimes based on the mean of each of the meteorological variables across all sites.

The best performing two-step model is based on the errors of the best performing regime switching autoregressive model, with pressure and temperature as inputs to to the K-means clustering to form the individual regime modes.

All of the two-step models based on the various combinations of regime switching autoregressive models was found to improve the predictive performance of the underlying autoregressive model. Consideration of higher numbers of regime modes is found to reduce the predictive performance of the two-step model.

The additional consideration of field regime modes based on the mean of each of the meteorological variables across all of the sites for the vector autoregressive in the two-step model is found to provide negligible improvement if the individual regime mode is included in the underlying autoregressive model. For the case of the base autoregressive model without regimes as the underlying model, the inclusion field regime modes for the vector autoregressive in the two-step model is found to provide a modest improvement.

As discussed in detail earlier in Section 2.5, making vector autoregressive models conditional to the meteorological conditions was shown by Tastu et al. (2010) [34] to improve the predictive performance. Tastu et al. (2010) benchmarked the additional percentage reduction in RMSE to WPPT, and reports that the making vector autoregressive models conditional to the wind speed and wind direction reduced the RMSE for the hour ahead by a further 0.72% to 3.5%. As Tastu et al. (2010) did not test an autoregressive model made conditional to the wind direction and wind speed, it is not clear if their reported improvements for making the model conditional to wind direction and wind speed would also be shown for an autoregressive model.

It is conjectured that consideration of the proposed field regime modes should further improve the predictive performance of the two-step model. However, this result is not found here, and may be attributed to splitting the data set into many sets which reduces the quality of the fit of the model due to insufficient number of data points. Regularisation may mitigate this issue enabling better fitting of the model given the higher parameter to datapoint ratios involed with splitting the data into many discrete sets [55].

The MAE of the two-step model is 5.51% for 1 hour ahead and increases to 6.53% at 6 hours ahead. The RMSE of the two-step model is 11.13% for 1 hour ahead and increases to 12.67% at 6 hours ahead. The percentage improvement in MAE and RMSE of the two-step model over each of the other respective models is shown below in Figure 12. The deterioration of predictive performance is extremely slow and significantly outperforms the state-of-the-art in research at several hours ahead [10].

There is some dispersion in forecast performance for the individual wind farms. The individual MAE of the two-step model ranges from 3.13% to 7.44% for 1 hour ahead and increases to values from 3.68% to 8.80% at 6 hours ahead. The individual RMSE of the two-step model ranges from 5.99% to 13.72% for 1 hour ahead and increases to values from 7.84% to 14.10% at 6 hours ahead. The variance in individual performance is quite consistant accross all of the proposed forecasting models, reflecting the variance is attributable to the variability and related difficulty in forecasting of the wind farms [30]. This shows the importance of benchmarking model performance to other models rather than comparing MAE and RMSE measures directly from wind farm to another, even for those within the same case study, as discussed in detail earlier in Section 2.4.

The percentage reduction in MAE of the two-step model over the base autoregressive model benchmark is 4.6% for 1 hour ahead and increases to 34.1% at 6 hours ahead. The percentage reduction in RMSE of the two-step model over the base autoregressive model benchmark is 0.6% for 1 hour ahead and increases to 21.8% at 6 hours ahead. The smaller percentage improvement in RMSE compared to MAE for the first hour ahead reflects the existence of small numbers of large forecast errors.

In comparison, Calvalcante et al. (2017) [31] reported a percentage reduction in RMSE over an autoregressive model benchmark of 5.7% at 1 hour ahead, which increases to 7% at 3 hours head, and then fades to 4% at 6 hours ahead. The slower deterioration of forecast skill at longer time horizons reflects that the spatio-temporal information persists over these time horizons. The quality of the spatio temporal information is reflected in Figure 4 shown earlier showing very strong cross-correlation at lags up to 12 hours. The cross-correlation information shown in Calvalcante et al. (2017) are weaker and fade faster after 3 hours, which is reflected in the deterioration of their forecast skill with time. The greater improvement in RMSE of Calvalcante et al. (2017) for the first hour is conjectured to be attributed to the superior fit of their model by the use of regularisation achieved with the least absolute shrinkage and selection operator framework. It is interesting to note that Calvalcante et al. (2017) reported a reduction in MAE over an autoregressive model benchmark of 7.54% at 1 hour ahead compared to the 4.6% reduction at 1 hour ahead for the propose two-step model which is not substantially different.

The percentage reduction in MAE of the two-step model over the regime switching autoregressive model benchmark is 0.8% for 1 hour ahead and increases to 2.4% at 6 hours ahead. The percentage reduction in RMSE of the two-step model over the regime switching autoregressive model benchmark is 1.3% for 1 hour ahead and increases to 3.4% at 6 hours ahead. While

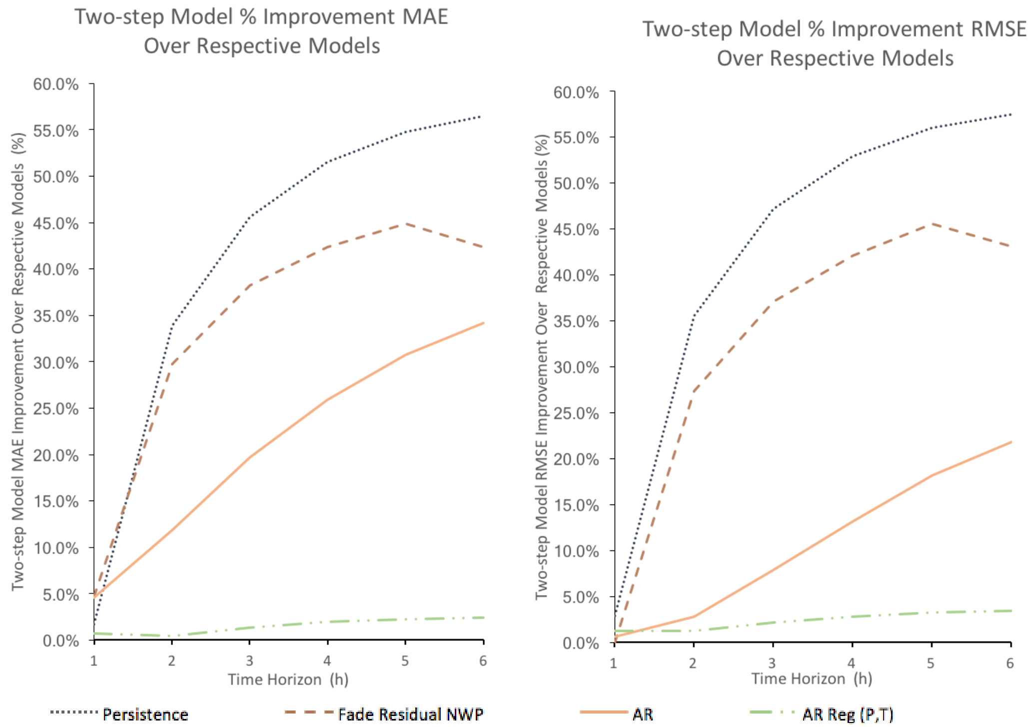

Figure 12: Mean Absolute Error (MAE) Normalised to Installed Capacity and Root Mean Squared Error (RMSE) Normalised to Installed Capacity Percentage Improvement of Two-Step Model Over Each Other Respective Model

these improvements are modest, the regime switching autoregressive model can be considered among the state-of-the-art approaches for point forecasts [15] [16], and even modest reductions in forecast error at the hour ahead can equate to subtantial monetary value in terms of reduced balanacing costs [5].

Each of the proposed models and associated features that lead to key improvements in the forecasts are reflected in Figure 11 and Figure 12. The consideration of the measured wind power directly into the autoregressive model showed significant improvements compared to the consideration of observed forecast error based on a NWP model. Making the autoregressive models conditional to the weather conditions through the regimes produced another substantial improvement in forecast skill. Finally, the two-step model capturing spatio-temporal aspects through vector autoregression improved the performance of the regime switching autoregressive models.

The 1 hour ahead forecast errors of the best performing regime switching two-step model for one of the wind farms over the whole of 2016, and a histogram showing the distribution of these forecast errors are shown below in Figure 13 and Figure 14 respectively. The wind farm chosen has a the median of forecast performance out of the set of wind farms. The distribution of the forecast errors is approximately Gaussian. A short summary of the distribution of forecast errors follows: 59% of the forecast errors are within +/- 5%, 79% of the forecast errors are within +/- 10%, 93.8% of the forecast errors are within +/- 20%, and 99.5% of the forecast errors are within +/- 40%.

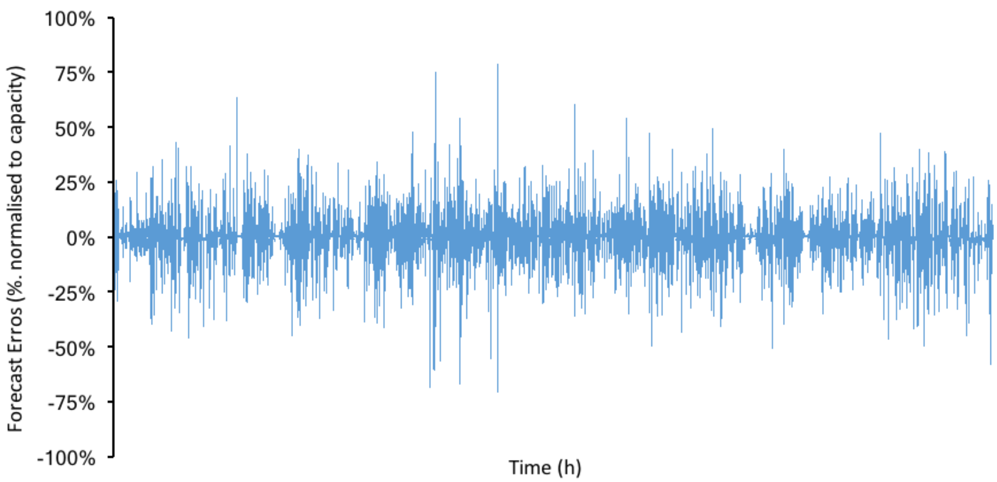

Figure 13: One Hour Ahead Forecast Errors of the Regime Switching Two-step Model for One Wind Farm for Every Hour of 2016

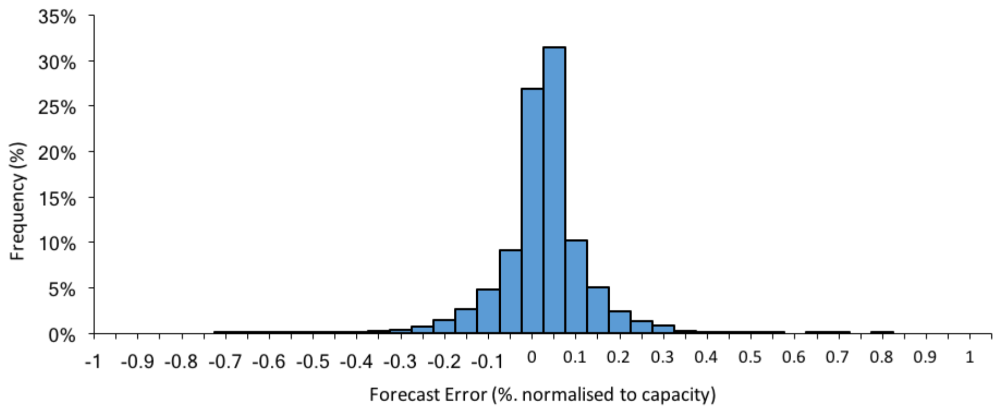

Figure 14: Histogram of One Hour Ahead Forecast Errors of the Regime Switching Two-step Model for One Wind Farm for All Hours of 2016

The regime switching two-step model hour ahead forecasts and the measured wind power are shown for illustrative purposes for the same wind farm for a randomly chosen week in 2016 below in Figure 15. The wind farm values are normalised to the installed capacity for data privacy.

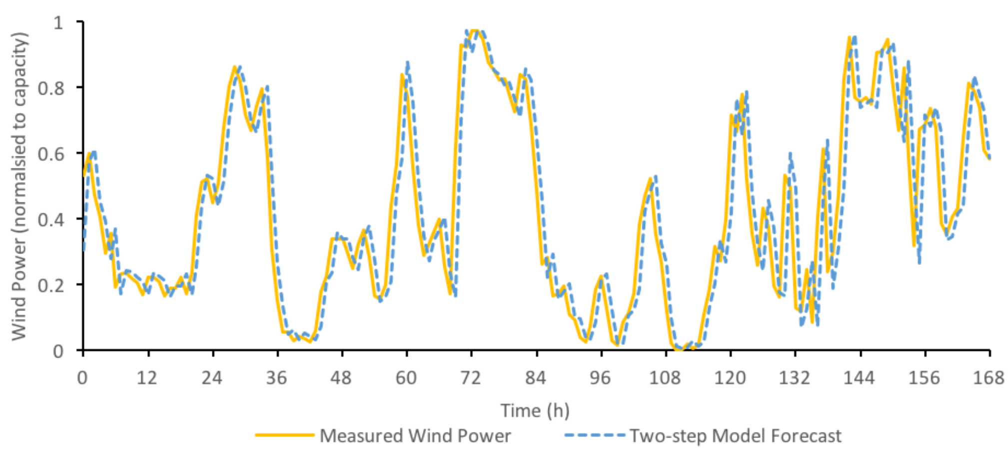

Figure 15: Measured Wind Power and Regime Switching Two-step Model 1 Hour Ahead Forecast Normalised to Installed Capacity for a Randomly Chosen Week in 2016.

While short term wind power forecasting with emphasis on statistical methods is usually only evaluated for the first 6 hours ahead, it can be interesting to examine the performance over longer time horizons. The performance of the two-step model from 1 hour ahead to 36 hours ahead in terms of MAE and RMSE is shown below in Figure 16. The model shows quite strong performance from 2 hours ahead up to 12 hours ahead before a wind power forecasting model with more emphasis on NWP inputs would take over with better predictive skill [10]. This improvement in forecast skill over the 2 hours ahead to 12 hours ahead can translate to more efficient and economic intra-day dispatch operations and planning.

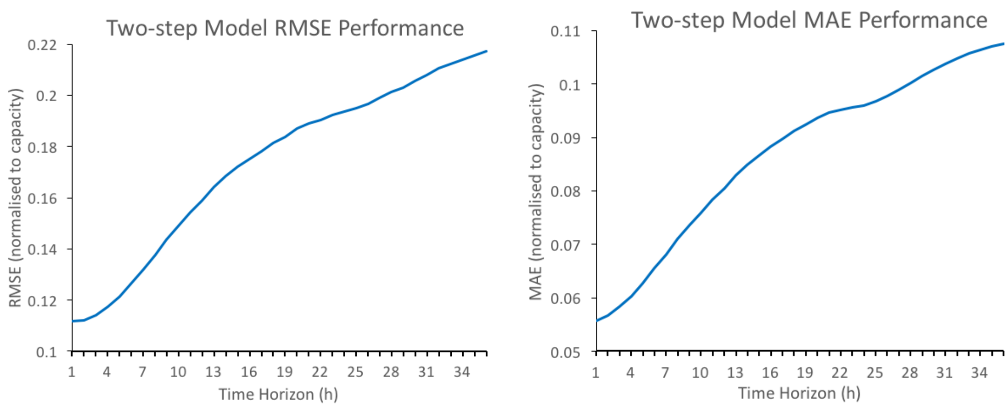

Figure 16: Mean Absolute Error (MAE) Normalised to Installed Capacity and Root Mean Squared Error (RMSE) Normalised to Installed Capacity of Regime Switching Two-step Model

5. Discussion

5.1. Contribution and Significance

This master thesis contributes to the limited research on spatio-temporal aspects for short term wind power forecasting, examining time series models focusing on incorporating spatio-temporal aspects conditional to meteorological conditions. It has been shown that the inclusion of spatio-temporal aspects consistently improves the state-of-the-art in wind power forecasting. The promising performance encourages further examination of spatio-temporal aspects.

Novel regime switching autoregressive and vector autoregressive models are proposed. The best performing two-step model utilises an underlying regime switching autoregressive model with a vector autoregressive model to take advantage of cross-correlation between sites incorporating upstream online wind power measurement information from all wind farms within a given region. The proposed novel regimes are formed using K-means clustering based on forecast meteorological conditions and show significant improvements in forecast skill for all of the time-series models.

The case-study thoroughly examines the performance of each of the proposed models. The strong performance of the models from 2 hours ahead up to 12 hours ahead reflects the quality of the proposed regimes as well as the quality of the underlying spatio-temporal information. This shows the importance of matching the spatial and temporal scales to capture the spatio-temporal aspects. The hourly resolution here is seen to be appropiate for the majority of the wind farms within a 300 km x 300km area. Shorter temporal resolution would likely improve the forecast performance of wind farms within a 50 km x 50 km of each other for very short time horizons up to 1 hour ahead. This consideration of matching spatial and temporal scales is one that has lacked in previous research, such as in he et al. (2014) [51], He et al. (2015)[52] and Dowell and Pinson (2016) [32], as discussed earlier in Section 2.5.

The model was implemented into the .NET framework of Vitec Software's Aiolos Forecast Studio, which is widely used in Northern and Western Europe. All of the proposed models were found to have significantly lower mean absolute error and root mean squared error compared to the Aiolos model and autoregressive model benchmarks. The proposed regime switching autoregressive model is ready to be implemented in Aiolos Forecast Studio with little work. The proposed two-step model is different to current Aiolos Forecast Studio design and would require additional changes to the user interface before being able to be implemented. It is hoped the promising results of the vector autoregressive model are to be further investigated by Vitec, namely the inclusion of regularisation in the fitting process and the consideration of shorter time resolution case studies.

The improved short term wind power forecast available to Vitec will inform operation and trading decisions and translate to significant reductions in balancing costs for Vitecs Aiolos Forecasting Studio customer's consisting of transmission system operators, distribution system operators, power producers, retailers, and traders. An estimate of this value is difficult to estimate as much of the data required is not publicly available. A simple estimate of the value of the improved wind power forecasts for Vitec's customers is estimated here to give an idea of the order of magnitude of the benefits. Vitec currently produces forecasts for approximately 12 GW of installed capacity of wind power with an estimated capacity factor of 0.3. The prosed regime switching vector autoregressive model reduces the mean absolute foreast error at 1 hour ahead by 4.7% and at 2 hours ahead by 29.8% compared to the current Aiolos wind power forecast with real time corrections. The system balancing costs due to wind power forecast error is between 1 to 4.5 Euro / MWh for wind penetrations of up to 20% of gross energy demand; this is approximately up to 10% of the wholesale value of the wind energy [4]. If the consideration of wind power forecasts for system operation and planning is conducted within the hour ahead or within two hours a head, the improvement is valued at as much as between 9.4 million Euros to 42.3 million Euros in reduced balancing costs. As similar improvements have been shown for the consideration of spatio-temporal aspects down to 5 minutes ahead, these reductions in balancing costs hold for shorter time horizons [32]. Hodge et al. (2015) [56] and Xie et al. (2014) [57] present more detailed evaluations of significant value of more accurate forecasting.

5.2. Limitations and Future Research and Development

A limitation of the proposed vector autoregressive models is the use of ordinary least squares as the fitting method without regularisation. It is conjectured that the generally weaker performance of the direct base vector autoregressive models compared to base autoregressive models is explained by poor fitting of the model using ordinary least squares without regularisation. Regularsation induces sparsity into the parameter matrix enabling better generalisation and mitigating the potential weakness of ordinary least sqaures to overfit problems in high parameter spaces [55]. The least absolute shrinkage and selection operator or ridge regression are potential penalty parameters to extend the fitting method to include regularisation [54]. He et al. (2015) [52], Dowell and Pinson (2016) [32] and Cavalcante et al. (2017) [31] all utilise regularisation in the fitting of their respective models. This limitation was partially overcome by use of the two-step model reducing the difficulty of fitting the vector autoregressive problem by effectively removing the strong autoregressive components. However, it is likely poor fitting methodology did not allow the field regime modes in the two-step model to contribute significantly to better capturing the spatio-temporal propagation of the forecast errors from the regime switching autoregressive model.

Reasonable computational performance, is achieved for the proposed models, with fitting times all less than 1 minute. Parallelism and efficient fitting algorithms are not required for the relatively small case study of hourly resolution for 24 wind farms and thus is not studied here, it is a prudent future extensions for the consideration of significantly larger data sets with smaller time resolution and more wind farms as the fitting problem grows with the square of the number of wind farms considered, increasing difficulty of fitting the problem and computation expense. The model can be extended to utilise parallism and more rapid convergence by solving the problem with alternating direction method of multipliers as proposed by Calvalcante et al. (2017) [31]. Calvalcante et al. (2017) achieve good computational performance with time required to fit the model on the order of seconds for the case study with hourly data for 66 wind farms located in the same control area.

The match of spatial and temporal scales is proposed here to be very important in the consideration of spatio-temporal aspects for improving prediction performance. This requires further investigation to establish which temporal resolutions are best suited to which spatial scales and geographic dispersion for optimal prediction perforance. Few studies explicitly tackle the problem of how spatio-temporal correlation changes with the averaging period as most studies consider a single temporal resolution when investigated spatio-temporal correlations. Louie et al. (2014) [58] and St. Martin et al.(2015) [59]report correlation decreases with the averaging period and decreases exponentially with separation distance. All averaging periods under 38 hours exhibit a distance at which wind power becomes uncorrelated that is proportional to the averaging period. Shorter averaging periods become uncorrelated for shorter distances.

It is interesting to note in one study for solar power, Perez et al. (2012)

examined the distance at which fluctuations of the clear sky index became uncorrelated for various temporal resolutions, and found a resolution of 20 seconds, 1 minute, 5 minutes, and 15 minutes became uncorrelated at distances of 500 m, 1 km, 4 km and 10 km respectively. These distances reflect the limits the consideration of spatio-temporal information can improve solar power forecasts. While solar power is clearly a function of very different processes to wind power, these spatio-temporal aspects are related mostly to the propagation of clouds, which in turn are a function of wind speed, so some parallels may be conjectured.

Regarding the inclusion of spatio-temporal aspects for time series models, erroneous measured data from one wind farm or changes in the farms production that are not related to the meteorological conditions have potential to harm the forecast quality for other wind farms and can be seen as a significant limitation. For implementation of spatio-temporal forecasts, the preprocessing of incoming production data is very important to the reliability of the forecasts and preprocessing standards should be developed and no such standards currently exist [28].

Making the models conditional to the meteorological conditions through the proposed regimes encourages continued research and development of alternative model approaches, as also called for by Tastu et al.(2010) [34], Dowell and Pinson (2016) [32] and Cavalcante et al. (2017) [31]. The path weather systems follow as they propagate through space and time is due to pressure differentials and is not in the same direction as the wind direction nor is the speed the same as the wind speed. Wind direction and wind speed alone can not always capture the evolution of the meteorological processes and can potentially explain why the regimes based only on pressure and temperature has showed marginally superior performance to those based on wind speed and wind direction. Topological features such as mountains, valleys and trees can funnel wind flow and can result in large changes to the wind direction at the surface compared to the geostrophic wind direction and wind speed. Thus regimes based on geostrophic wind speeds and directions together with atmospheric stability would be interesting to investigate. Hidden Markov-Regime switching models based on an unobservable process have showed superior performance over threshold regime switching models based on observable lagged values [17] [16]. It would be interesting for Markov-Regime switching models to be compared to the proposed K-means clustering regimes in future research.

6. Conclusion

The proposed novel models are successfully implemented into the .NET framework of Vitec Software's Aiolos Forecast Studio, which is widely used in Northern and Western Europe. The proposed short term wind power forecasting time series models made conditional to meteorological conditions and which incorporate spatio-temporal aspects show significant improvements in forecast skill. This is reflected by significant reductions in mean absolute error and root mean squared error compared to the Aiolos model and autoregressive model benchmarks. The vector autoregressive framework in the proposed two-step model is able to take advantage of cross-correlation between sites incorporating upstream online production information from all wind farms within a given region. The regimes are formed using K-means clustering based on forecast meteorological conditions, with regimes based on wind speed, and the combination of pressure and temperature showing the best ability to characterize the regimes to improve the predictive performance. Appropriate matching of spatial and temporal scale is important to achieving full performance of spatio-temporal wind power forecasting models. The selected case study shows a good match between spatial and temporal scales as reflected by the high cross correlations between the sites and strong performance of the two-step model up to a lead time of 12 hours ahead.

The improved short term wind power forecasts will inform operation and trading decisions and translate to significant reductions in balancing costs for Vitecs customers. The improvement is valued at as much as between 9.4 million Euros to 42.3 million Euros in reduced balancing costs. Spatio-temporal aspects conditioned to meteorological conditions for wind power forecasting shows to be promising for improving current state-of-the-art wind power forecasting, reducing balancing costs, and ultimately facilitating the continued integration of wind power.

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